# Graph Connectivity Using Star Contraction (logs Matter)

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# **Model of Computation**

# Cut queries – Min Cut

• Given  $G = (V, E)$ , access via *cut queries:* 

 $S \subseteq V \Rightarrow |E(S, V \setminus S)|$ 

- $\cdot$  **Goal**: find a minimum cut, denoted  $C$ .
- $\delta$  minimum degree
- $\lambda$  edge connectivity



## Cut queries – Min Cut

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**Trivial:**  $O(n^2)$ , learn the graph.  $|E(S,T)|$  in  $O(1)$  queries.

# Motivation – Submodular function minimization

- $F: 2^V \to \mathbb{R}$  is sub-modular if  $\forall S, T \in 2^V, F(S) + F(T) \geq F(S \cup T) + F(S \cap T)$
- Query access.
- Goal: find arg ming  $\overline{\text{SE2}^V}$  $F(S).$
- Examples:
	- **Graph cuts,**  $F(S) = |\partial S|$
	- Entropy
	- Mutual Information
	- Matroid rank

#### Diminishing marginal gain



Slides inspired by and figures taken from https://people.csail.mit.edu/stefje/mlss/kyoto\_mlss\_lecture1.pdf

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- Query access.



# Motivation – Symm Submodular function minimization



 $Cut(A) = Cut(V - A)$ 

**Global Min-cut**: Goal is **non-trivial minimizer**

 $\boldsymbol{S}$ 

 $Cut(A) \neq Cut(V - A)$ 

 $(s, t)$ -Min-cut = Max-Flow  $\Leftarrow$  Bipartite matching

# SFM – Previous work, upper bounds



# SFM – Previous work, upper bounds



# SFM – Previous work, Lower bounds



Lower bound situation is dire!

What problems are suitable for proving high SFM lower bound?

# Previous Work

- **Connectivity** in  $O(n \log n)$  cut queries **[Harvey 2008]**
- Unweighted minimum cut in  $O(n \log^3 n)$  cut queries **[Rubinstein, Schramm, Weinberg 2018]**
- **Multigraph** minimum cut in  $O(n \log^4 n)$  cut queries **[M, Nanongkai 2020]**



- $\Omega\left(\frac{n}{\log n}\right)$  $\left(\frac{n}{\log n}\right)$  cut queries for **Connectivity**,  $\Omega(n)$  assuming communication complexity conjecture of **[Babai, Frankl, Simon 1986]**
- $\Omega\left(\frac{n\log\log n}{\log n}\right)$  $\frac{\log \log n}{\log n}$ ) cut queries for minimum cut on simple graphs. **[Assadi, Dudeja 2021]**



Main Result

**Theorem.** Randomised cut-query algorithm for min-cut in simple graphs has  $O(n)$  complexity.

Improves state of the art even for connectivity!

Tight under conjecture of **[Babai, Frankl, Simon 1986]**

**Other applications:** Matrix-vector queries, semi streaming etc.

Main Result

**Theorem.** Randomised cut-query algorithm for min-cut in simple graphs has  $O(n)$  complexity.





# Background: Cut Query Primitives



# Background: Basic Algorithm



- Pack  $\delta$  spanning trees.
	- Each tree must cross every cut at least once.
	- $\delta \geq \lambda$ .
- Complexity:  $\tilde{O}(n\delta) \rightarrow O(n\delta)$ .

Separating matrices

• Can we do any better?

# Background: Min-cut Preserving Clustering **[Kawarabayashi, Thorup 2015]**



- Simple graph  $G$  with min deg  $\delta$ .
- Contract:  $G \rightarrow G'$  such that
	- $G'$  has  $\tilde{O}\left(\frac{n}{\delta}\right)$  vertices and  $\tilde{O}(n)$ edges.
	- All non-trivial min-cuts are preserved.

#### Min-cut  $(G)$  = Min-cut  $(G')$

- Pack  $\delta$  spanning trees in  $G'$ 
	- Linear complexity



• Let  $C$  be some min cut. Every vertex  $v$ chooses uniformly random neighbor  $u \in N(v)$ .



- Let  $C$  be some min cut. Every vertex  $v$ chooses uniformly random neighbor  $u \in N(v)$ .
- **- sampled edges.**
- Pr $[S \cap C = \emptyset]$ ?

• 
$$
\Pr[S \cap C = \emptyset] \ge \frac{1^4}{2} = \frac{1}{16}
$$

• Constant Prob!



- Let  $C$  be some min cut. Every vertex  $v$ chooses uniformly random neighbor  $u \in N(v)$ .
- S- sampled edge

• 
$$
Pr[S \cap C = \emptyset] =
$$

$$
\prod_{v \in N(C)} \left(1 - \frac{c(v)}{d(v)}\right)^{\sum}
$$

≥

1

16

$$
\frac{c(v)}{d(v)} \le 1/2 \text{ for every } v \in N(C)
$$

$$
\sum_{v \in N(C)} \frac{c(v)}{d(v)} \le 2\frac{|C|}{\delta(G)} \le 2.
$$

$$
G = (V, E)
$$
  
1-out sample + contract edges  

$$
G' = (V', E')
$$

- With constant probability,  $\lambda(G) = \lambda(G')$
- Solve on multigraph  $G'$ ?
- One can show: Exists graphs s.t.  $=\Theta\left(\frac{n}{\sqrt{2}}\right)$  $\frac{\epsilon}{\delta}$ ) w.h.p.

We want: 
$$
O\left(\frac{n}{\delta}\right)
$$

# Background: **Two**-out contraction **[Ghaffari, Nowicki, Thorup 2020]**



### Star-Contraction

- Idea: Sample from a subset of neighbors
- **Construct set** *R* **with each**  $v \in R$  **w.p.**  $p = \Theta\left(\frac{\log n}{s}\right)$
- Each  $u \notin R$  independently samples neighbor  $v$  $\in N_R(u)$
- Contract sampled edges S into  $G' = (V', E').$

$$
\mathbb{E}_R\left[\frac{c_R(v)}{d_R(v)}\middle| d_R(v) > 0\right] = \frac{c(v)}{d(v)}
$$



# Star-Contraction

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- **Each**  $u \notin R$  independently samples neighbor  $v$  $\in N_R(u)$
- Contract sampled edges S into  $G' = (V', E').$

• **Immediate:** 
$$
|V'| = O\left(\frac{n \log n}{\delta}\right)
$$
 w.h.p.

- Pr[ $S \cap C = \emptyset$ ] =  $\Omega(1)$ .
- $\lambda(G') = \lambda(G)$  with constant probability!

**Complexity**: 
$$
O\left(\frac{n}{\delta}\log n \cdot \delta\right) = O(n \log n)
$$
.



# Beyond  $n \log n$  step 1: Refined star contraction

- $|R|$  and therefore  $|V'|$  are too large
- Replace  $p = \Theta\left(\frac{\log n}{\delta}\right)$  with  $p = \Theta\left(\frac{\log \delta}{\delta}\right)$
- **Immediate:**  $|R| = O\left(\frac{n \log \delta}{s}\right)$  $\delta$
- $|V^*| = |\{ v \in V \mid N(v) \cap R = \emptyset\}| = O\left(\frac{n}{s}\right)$  $\boldsymbol{\delta}$
- $V' = R \cup V^*$
- Each  $u \notin V'$ , independently samples neighbor  $v \in N_R(u)$
- Contract into  $G' = (V', E')$
- $O(n \log \delta) \Rightarrow O(n \log \log n)$  queries.



#### If  $\delta \geq polylog(n)$ , use **[Mukhopadhyay, Nanongkai 2020]**

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- $V' = R \cup V^*$
- Each  $u \notin V'$ , independently samples neighbor  $\leftarrow$  $v \in N_R(u)$ **Separating Matrices Trivial:**
- Contract into  $G' = (V', E')$
- $O(n \log \delta) \Rightarrow O(n \log \log n)$  queries.

**How?**

The Problem Each  $u \notin V'$  independently samples neighbor  $v \in N_R(u)$ 

$$
\Pr[S \cap C = \emptyset] = \prod_{v \in N(C)} \left( 1 - \frac{c(v)}{d(v)} \right) > \frac{1}{16} \text{ as long as}
$$
\n
$$
\frac{c(v)}{d(v)} \le 1/2 \text{ for every } v \in N(C)
$$
\n
$$
\sum_{v \in N(C)} \frac{c(v)}{d(v)} \le 2 \frac{|C|}{\delta(G)} \le 2.
$$

 $q_u = \Pr_{v:(u,v)\in A}[\{u,v\} \in C]$   $(\alpha,\beta)$ -good for contraction if:

1. max property:  $\max_u q_u \leq \alpha$ , and  $Pr[S \cap C = \emptyset] = (1 - \alpha)^{\lceil \beta / \alpha \rceil}.$ 2. sum property:  $\sum_{u} q_u \leq \beta$ .







# The Problem Each  $u \in S$  independently samples neighbor  $v \in T$







- $|S| \times |T|$  Boolean matrix M,  $M[u, v] = 1 \leftrightarrow (u, v) \in E$
- *M* has row sparsity  $\ell$
- Goal, learn M!

**Seperating Matrices:** Learn  $M \in \{0,1\}^{n \times n}$  of row sparsity  $\ell$  with  $O(\ell n)$  cut queries



**Seperating Matrices:** Learn  $M \in \{0,1\}^{n \times n}$  of row sparsity  $\ell$  with  $O(\ell n)$  cut queries

- **Trivial:**  $O(\ln \log n)$  cut queries using binary search.
- A cut query provides  $\Omega(\log n)$  bit of information.
- Can be used to shave the log factor.



- **Learn**  $M \in \{0, 1\}^{n \times n}$  of row sparsity  $\ell$  with  $O(\ell n)$  cut queries
- **Sampling Lemma:** Solve **The (Easy) Problem** in  $O(|S|)$  cut queries, **in expectation**
- Immediate corollary: **Connectivity** in **expected**  $O(n)$  cut queries!
- Lemma solves The Problem as well in expected  $O(n)$  cut queries!  $\cdot$

Degree buckets  $[2^i, 2^{i+1}]$ Sample w.p.  $\frac{1}{2^i}$  for  $O(1)$ sparsity

Remains  $(\alpha, \beta)$ good

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# Beyond  $n \log \log n$

- Need to have  $O\left(\frac{n}{s}\right)$  $\left(\frac{n}{\delta}\right)$  vertices within  $O(n)$  complexity.
- From  $O\left(\frac{n \log \delta}{\delta}\right)$  to  $O\left(\frac{n}{\delta}\right)$ :
	- Learn a dense enough subgraph with  $O(n)$  queries.
	- Do 2-out contraction within it.

**Theorem.** Randomised cut-query algorithm for min-cut in simple graphs has  $O(n)$  complexity.

Thank you!

Open Questions:

- Randomised communication complexity of edge connectivity?
	- SOTA:  $\Omega(n \log \log n)$  [AD21]
- Zero-error/Deterministic edge connectivity with  $O(n)$  cut queries?
- Weighted graph:  $O(n)$  cut query?
- In general: SFM needs  $\omega(n)$  evaluation query accesses?