# CMPSCI 711: More Advanced Algorithms Section 2-1: Graph Streams 

Andrew McGregor

Last Compiled: April 29, 2012

## Graph Streams

- Consider a stream of $m$ edges

$$
\left\langle e_{1}, e_{2}, \ldots \quad \ldots, e_{m}\right\rangle
$$

defining a graph $G$ with nodes $V=[n]$ and $E=\left\{e_{1}, \ldots, e_{m}\right\}$

- Massive graphs include social networks, web graph, call graphs, etc.
- What can we compute about $G$ in $o(m)$ space?
- Focus on semi-streaming space restriction of $O(n \cdot$ polylog $n$ ) bits.


## Warm-Up: Connectivity

- Goal: Compute the number of connected components.
- Algorithm: Maintain a spanning forest $F$
- $F \leftarrow \emptyset$
- For each edge $(u, v)$, if $u$ and $v$ aren't connected in $F$,

$$
F \leftarrow F \cup\{(u, v)\}
$$

- Analysis:
- $F$ has the same number of connected components as $G$
- $F$ has at most $n-1$ edges.
- Thm: Can count connected components in $O(n \log n)$ space.


## Extension: $k$-Edge Connectivity

- Goal: Check if all cuts are of size at least $k$.
- Algorithm: Maintain $k$ forests $F_{1}, \ldots, F_{k}$
- $F_{1}, \ldots, F_{k} \leftarrow \emptyset$
- For each edge $(u, v)$, find smallest $i \leq k$ such that $u$ and $v$ aren't connected in $F_{i}$,

$$
F_{i} \leftarrow F_{i} \cup\{(u, v)\}
$$

If no such $i$ exists, ignore edge.

- Analysis:
- Each $F_{i}$ has at most $n-1$ edges so total edges is $O(n k)$
- Lemma: $\operatorname{Min-Cut}(V, E)<k$ iff $\operatorname{Min-Cut}\left(V, F_{1} \cup \ldots \cup F_{k}\right)<k$
- Thm: Can check $k$-connectivity in $O(k n \log n)$ space.


## Proof of Lemma

- Let $H=\left(V, F_{1} \cup \ldots \cup F_{k}\right)$ and let $(S, V \backslash S)$ be an arbitrary cut.
- Since $H$ is a subgraph:

$$
\left|E_{G}(S)\right| \geq\left|E_{H}(S)\right|
$$

where $E_{H}(S)$ and $E_{G}(S)$ are the edges across the cut in $H$ and $G$

- Suppose there exists $(u, v) \in E_{G}(S)$ but $(u, v) \notin F_{1} \cup \ldots \cup F_{k}$. Then $(u, v)$ must be connected in each $F_{i}$. Since $F_{i}$ are disjoint,

$$
\left|E_{H}(S)\right| \geq \min \left(\left|E_{G}(S)\right|, k\right)
$$

## Spanners

## Definition

An $\alpha$-spanner of graph $G$ is a subgraph $H$ such that for any nodes $u, v$,

$$
d_{G}(u, v) \leq d_{H}(u, v) \leq \alpha d_{G}(u, v) .
$$

where $d_{G}$ and $d_{H}$ are the shortest path distances in $G$ and $H$ respectively.

- Algorithm:
- $H \leftarrow \emptyset$.
- For each edge $(u, v)$, if $d_{H}(u, v) \geq 2 t, H \leftarrow H \cup\{(u, v)\}$
- Analysis:
- Distances increase by at most a factor $2 t-1$ since an edge $(u, v)$ is only forgotten if there's already a detour of length at most $2 t-1$.
- Lemma: $H$ has $O\left(n^{1+1 / t}\right)$ edges since all cycles have length $\geq 2 t+1$.

Theorem
Can (2t-1)-approximate all distances using only $O\left(n^{1+1 / t}\right)$ space.

## Proof of Lemma

## Lemma

$A$ graph $H$ on $n$ nodes with no cycles of length $\leq 2 t$ has $O\left(n^{1+1 / t}\right)$ edges.

- Let $d=2 m / n$ be the average degree of $H$.
- Let $J$ be the graph formed by removing nodes with degree less than $d / 2$ until no such nodes remain.
- $J$ is not empty because $<m /(d / 2)=n$ nodes can be removed.
- Grow a BFS of depth $t$ from an arbitrary node in $J$.
- Because a) no cycles of length less than $2 t+1$ and b) all degrees in $J$ are at least $d / 2$, number of nodes at $t$-th level of BFS is at least

$$
(d / 2-1)^{t}=(m / n-1)^{t}
$$

- But $(m / n-1)^{t} \leq|J| \leq n$ and therefore,

$$
m \leq n+n^{1+1 / t}
$$

## Sparsifier

## Definition

An $\alpha$-sparsifier of graph $G$ is a weighted subgraph $H$ such that for any cut $(S, V \backslash S)$,

$$
C_{G}(S) \leq C_{H}(S) \leq \alpha C_{G}(S) .
$$

where $C_{G}$ and $C_{H}$ is the capacity of the cut in $G$ and $H$ respectively.
Theorem (Batson, Spielman, Srivastava)
There exists a (non-streaming) algorithm $\mathcal{A}$ that constructs a $(1+\epsilon)$-sparsifier with only $O\left(n \epsilon^{-2}\right)$ edges.

Idea for stream algorithm is to use $\mathcal{A}$ as a black box to "recursively" sparsify the graph stream.

## Basic Properties of Sparsifiers

Lemma
Suppose $H_{1}$ and $H_{2}$ are $\alpha$-sparsifiers of $G_{1}$ and $G_{2}$. Then $H_{1} \cup H_{2}$ is an $\alpha$-sparsifier of $G_{1} \cup G_{2}$.

Lemma
Suppose $J$ is an $\alpha$-sparsifiers of $H$ and $H$ is an $\alpha$-sparsifier of $G$. Then $J$ is an $\alpha^{2}$-sparsifier of $G$.

## Stream Sparsification

- Divide length $m$ stream into segments of length $t=O\left(n \epsilon^{-2}\right)$
- Let $G_{0}, G_{1}, \ldots, G_{m / t-1}$ be graphs defined by each segment and let

$$
G_{0}^{1}=G_{0} \cup G_{1}, G_{2}^{1}=G_{2} \cup G_{3}, \ldots, G_{m / t-2}^{1}=G_{m / t-2} \cup G_{m / t-1}
$$

and for $i>1$,

$$
G_{j 2^{i}}^{i}=G_{j 2^{i}} \cup G_{j 2^{i}+1} \cup \ldots \cup G_{j 2^{i}+2^{i}-1}
$$

and note that $G_{0}^{\log m}=G$.

- Let $\tilde{G}_{j 2^{i}}^{j}$ be a $(1+\gamma)$-sparsifier of $\tilde{G}_{j 2^{i}}^{i-1} \cup \tilde{G}_{j 2^{i}+2^{i-1}}^{i-1}$ and $\tilde{G}_{j}=G_{j}$.
- Hence, $\tilde{G}_{0}^{\log n}$ is a $(1+\gamma)^{\log m}$-sparsifier of $G$.
- Can compute $\tilde{G}_{0}^{\log n}$ in $O\left(n \gamma^{-2} \log m\right)$ space.
- Setting $\gamma=\frac{\epsilon}{\log m}$ gives $(1+\epsilon)$-sparsifier in $O\left(n \epsilon^{-2} \log ^{3} m\right)$ space.


## Spectral Sparsification

- Given a graph $G$, the Laplacian matrix $L_{G} \in \mathbb{R}^{n \times n}$ has entries:

$$
L_{i j}= \begin{cases}\operatorname{deg}(i) & \text { if } i=j \\ -1 & \text { if }(i, j) \in E \\ 0 & \text { otherwise }\end{cases}
$$

- $H$ is an $(1+\epsilon)$ spectral sparsifier if for all

$$
\forall x \in \mathbb{R}^{n}, \quad(1-\epsilon) x^{\top} L_{G} x \leq x^{\top} L_{H} x \leq(1+\epsilon) x^{T} L_{G} X
$$

- Note that $x^{T} L_{G} X=\sum_{(i, j) \in E}\left(x_{i}-x_{j}\right)^{2}$ and hence $H$ is a $(1+\epsilon)$ sparsifier if

$$
\forall x \in\{0,1\}^{n}, \quad(1-\epsilon) x^{\top} L_{G} x \leq x^{\top} L_{H} x \leq(1+\epsilon) x^{\top} L_{G} x
$$

and therefore spectral sparsification is a generalization of ("cut" or "combinatorial") sparsification.

- Spectral sparsifiers also approximate eigenvalues. These relate to expansion properties, random walks, mixing times etc.

