A Simple, Space-Efficient, Streaming Algorithm for Matchings in Low Arboricity Graphs

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Abstract

We present a simple single-pass data stream algorithm using $O(\epsilon^{-2}\log n)$ space that returns a $(\alpha+2)(1+\epsilon)$ approximation to the size of the maximum matching in a graph of arboricity α.

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1 Introduction

We present a data stream algorithm for estimating the size of the maximum matching of a low arboricity graph. Recall that a graph has arboricity α if its edges can be partitioned into at most α forests and that a planar graph has arboricity $\alpha = 3$. Estimating the size of the maximum matching in such graphs has been a focus of recent data stream research [1–4, 6, 8]. See also [7] for a survey of the general area of graph algorithms in the stream model.

A surprising result on this problem was recently proved by Cormode et al. [4]. They designed an ingenious algorithm that returned a $(22.5\alpha + 6)(1 + \epsilon)$ approximation using a single pass over the edges of the graph (ordered arbitrarily) and $O(\epsilon^{-3}\cdot\alpha\cdot\log^2 n)$ space[1]. We improve the approximation factor to $(\alpha + 2)(1 + \epsilon)$ via a simpler and tighter analysis and show that, with a modification and simplification of their algorithm, the space required can be reduced to $O(\epsilon^{-2}\log n)$.

2 Results

Let $\mathsf{match}(G)$ be the maximum size of a matching in a graph G and let E_α be the set of edges uv where the number of edges incident to u or v that appear in the stream after uv are both at most α.

2.1 A Better Approximation Factor

We first show a bound for $\mathsf{match}(G)$ in terms of $|E_\alpha|$. Cormode et al. proved a similar but looser bound via results on the size of matchings in bounded degree graphs.

▶ **Theorem 1.** $\mathsf{match}(G) \le |E_\alpha| \le (\alpha+2)\,\mathsf{match}(G)$.

[1] Here, and throughout, space is specified in words and we assume that an edge or a counter (between 0 and α) can be stored in one word of space.

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Proof. We first prove the right inequality. To do this define $y_e = 1/(\alpha+1)$ if e is in E_α and 0 otherwise. Note that $\{y_e\}_{e\in E}$ is a fractional matching with maximum weight $1/(\alpha+1)$. A corollary of Edmonds' Matching Polytope Theorem [5] implies that its total weight is at most $(\alpha+2)/(\alpha+1)$ larger than the maximum integral matching. This corollary is likely well known but, for completeness, we include a proof of the corollary in the appendix. Hence,

$$\frac{|E_\alpha|}{\alpha+1} = \sum_e y_e \le \frac{\alpha+2}{\alpha+1} \cdot \mathsf{match}(G) \ .$$

It remains to prove the left inequality. Define H to be the set of vertices with degree $\alpha+1$ or greater. We refer to these as the *heavy* vertices. For $u \in V$, let B_u be the set of the last $\alpha+1$ edges incident to u that arrive in the stream.

Say an edge uv is *good* if $uv \in B_u \cap B_v$ and *wasted* if $uv \in B_u \oplus B_v$, i.e., the symmetric difference. Then $|E_\alpha|$ is exactly the number of good edges. Define

$$\begin{aligned} w &= \text{number of good edges with no end points in } H \ , \\ x &= \text{number of good edges with exactly one end point in } H \ , \\ y &= \text{number of good edges with two end points in } H \ , \\ z &= \text{number of wasted edges with two end points in } H \ , \end{aligned}$$

and note that $|E_\alpha| = w + x + y$.

We know $x + 2y + z = (\alpha+1)|H|$ because B_u contains exactly $\alpha+1$ edges if $u \in H$. Furthermore, $z + y \le \alpha|H|$ because the graph has arboricity α. Therefore

$$x + y \ge (\alpha+1)|H| - \alpha|H| = |H| \ .$$

Let E_L be the set of edges with no endpoints in H. Since every edge in E_L is good, $w = |E_L|$. Hence, $|E_\alpha| \ge |H| + |E_L| \ge \mathsf{match}(G)$ where the last inequality follows because at most one edge incident to each heavy vertex can appear in a matching. ◀

Let G_t be the graph defined by the stream prefix of length t and let E_α^t be the set of good edges with respect to this prefix, i.e., all edges uv from G_t where the number of edges incident to u or v that appear after uv in the prefix are both at most α. By applying the theorem to G_t, and noting that $\max_t |E_\alpha^t| \ge |E_\alpha|$ and $\mathsf{match}(G_t) \le \mathsf{match}(G)$, we deduce the following corollary:

▶ **Corollary 2.** *Let* $E^* = \max_t |E_\alpha^t|$. *Then* $\mathsf{match}(G) \le E^* \le (\alpha+2)\,\mathsf{match}(G)$.

2.2 A Simpler Algorithm using Smaller Space

See Figure 1 for an algorithm that approximates E^* to a $(1+\epsilon)$-factor in the insert-only graph stream model. The algorithm is a modification of the algorithm for estimating $|E_\alpha|$ designed by Cormode et al. [4]. The basic idea is to independently sample edges from E_α^t with probability that is high enough to obtain an accurate approximation of $|E_\alpha^t|$ and yet low enough to use a small amount of space. For every sampled edge $e = uv$, the algorithm stores the edge itself and two counters c_e^u and c_e^v for degrees of its endpoints in the rest of the stream. If we detect that a sampled edge is not in E_α^t, i.e., either of the associated counters exceed α, it is deleted.

Cormode et al. ran multiple instances of this basic algorithm corresponding to sampling probabilities $1, (1+\epsilon)^{-1}, (1+\epsilon)^{-2}, \ldots$ in parallel; terminated any instance that used too much space; and returned an estimate based on one of the remaining instantiations. Instead,

Algorithm 1: APPROXIMATING E^*
1. Initialize $S \leftarrow \emptyset$, $p = 1$, estimate $= 0$
2. For each edge $e = uv$ in the stream:
  a. With probability p add e to S and initialize counters $c_e^u \leftarrow 0$ and $c_e^v \leftarrow 0$
  b. For each edge $e' \in S$, if e' shares endpoint w with e:
    - Increment $c_{e'}^w$
    - If $c_{e'}^w > \alpha$, remove e' and corresponding counters from S
  c. If $|S| > 40\epsilon^{-2}\log n$:
    - $p \leftarrow p/2$
    - Remove each edge in S and corresponding counters with probability $1/2$
  d. estimate $\leftarrow \max(\text{estimate}, |S|/p)$
3. Return estimate

Figure 1 APPROXIMATING E^* Algorithm.

we start sampling with probability 1 and put a cap on the number of edges stored by the algorithm. Whenever the capacity is reached, the algorithm halves the sampling probability and deletes every edge currently stored with probability 1/2. This modification saves a factor of $O(\epsilon^{-1}\log n)$ in the space use and update time of the algorithm. We save a further $O(\alpha)$ factor in the analysis by using the algorithm to estimate E^* rather than $|E_\alpha|$.

▶ **Theorem 3.** *With high probability, Algorithm 1 outputs a $(1+\epsilon)$ approximation of E^*.*

Proof. Let k be such that $2^{k-1}\tau \le E^* < 2^k\tau$ where $\tau = 20\epsilon^{-2}\log n$. First suppose we toss $O(\log n)$ coins for each edge in E_α^t and say that an edge e is sampled at level i if at least the first $i-1$ coin tosses at heads. Hence, the probability that an edge is sampled at level i is $p_i = 1/2^i$ and that the probability an edge is sampled at level i conditioned on being sampled at level $i-1$ is $1/2$. Let s_i^t be the number of edges sampled. It follows from the Chernoff bound that for $i \le k$,

$$\mathbb{P}\left[|s_i^t - p_i|E_\alpha^t|| \ge \epsilon p_i E^*\right] \le \exp\left(-\frac{\epsilon^2 E^* p_i}{4}\right) \le \exp\left(-\frac{\epsilon^2 E^* p_k}{4}\right) \le \exp\left(-\frac{\epsilon^2\tau}{8}\right) = \frac{1}{\text{poly}(n)} .$$

By the union bound, with high probability, $s_i^t/p_i = |E_\alpha^t| \pm \epsilon E^*$ for all $0 \le i \le k$, $1 \le t \le \alpha n$.

The algorithm initially maintains the edges in E_α^t sampled at level $i = 0$. If the number of these edges exceeds the threshold, we subsample these to construct the set of edges sampled at level $i = 1$. If this set of edges also exceeds the threshold, we again subsample these to construct the set of edges at level $i = 2$ and so on. If i never exceeds k, then the above calculation implies that the output is $(1 \pm \epsilon)E^*$. But if s_k^t is bounded above by $(1+\epsilon)E^*/2^k < (1+\epsilon)\tau$ for all t with high probability, then i never exceeds k. ◀

It is immediate that the algorithm uses $O(\epsilon^{-2}\log n)$ space since this is the maximum number of edges stored at any one time. By Corollary 2, E^* is an $(\alpha+2)$ approximation of $\mathsf{match}(G)$ and hence we have proved the following theorem.

▶ **Theorem 4.** *The size of the maximum matching of a graph with arboricity α can be $(\alpha+2)(1+\epsilon)$-approximated with high probability using a single pass over the edges of G given $O(\epsilon^{-2}\log n)$ space.*

Acknowledgement. In an earlier version of the proof of Theorem 3, we erroneously claimed that, conditioned on the current sampling rate being $1/2^j$, edges in E_α^t had been sampled at that rate. Thanks to Sepehr Assadi, Vladimir Braverman, Michael Dinitz, Lin Yang, and Zeyu Zhang for catching this mistake.

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A Corollary of Edmonds' Theorem

For completeness, we include a simple corollary of Edmonds' Theorem used to prove Theorem 1. Recall that Edmonds' Theorem implies that if the weight of a fractional matching on any induced subgraph $G(U)$ is at most $(|U|-1)/2$, then the weight on the entire graph is at most $\mathsf{match}(G)$.

▶ **Lemma 5.** *Let $\{y_e\}_{e\in E}$ be a fractional matching where the maximum weight is ϵ. Then,*

$$\sum_e y_e \le (1+\epsilon)\,\mathsf{match}(G)\ .$$

Proof. Let U be an arbitrary subset of vertices and let $E(U)$ be the edges in the induced subgraph on U. Let $t=|U|$. Then since $|E(U)|\le t(t-1)/2$,

$$\sum_{e\in E(U)} y_e \le \min\left(\frac{t}{2},\epsilon|E(U)|\right) \le \frac{t-1}{2}\cdot\min\left(\frac{t}{t-1},\epsilon t\right) \le \frac{t-1}{2}\cdot(1+\epsilon)\ .$$

Hence, the fractional matching defined by $z_e = y_e/(1+\epsilon)$ satisfies $\sum_e z_e \le \mathsf{match}(G)$. Therefore, $\sum_e y_e \le (1+\epsilon)\sum_e z_e \le (1+\epsilon)\,\mathsf{match}(G)$. ◀