# An Asymptotically Optimal Algorithm for Maximum Matching in Dynamic Streams 

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Joint work with Sepehr Assadi

## Matching Problem

- Graph $G=(V, E)$
- Matching: $M \subseteq E,(V, M)$ has max degree 1
- Maximum matching: Matching $M^{*}$ of the largest size



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- Dynamic Stream: Insertions or Deletions
- Output a solution at the end of the stream
- Goal: Minimize Memory


## Lower Bound

- Maximum Matching Lower bound: $\Omega\left(n^{2}\right)$ bits [FKM+05]
- Store the input: $O\left(n^{2}\right)$ bits
- No non-trivial solution


## Approximation

- Question: What about an $\alpha$ approximation?
- Return a matching $M$ of size at least $\frac{\left|M^{*}\right|}{\alpha}$
- Can we get $o\left(n^{2}\right)$ space?
- What is the trade off between $\alpha$ and the space?


## Previous Work

| Result | Upper Bound | Lower Bound |  |
| :--- | :--- | :--- | :---: |
| $[$ Kon15] | $O\left(n^{2} / \alpha^{2}\right)$ | $\Omega\left(n^{1.5} / \alpha^{4}\right)$ |  |
|  |  |  |  |
|  |  |  |  |



Space-Approximation Tradeoff

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| $[D K 20]$ |  | $\Omega\left(n^{2} / \alpha^{3}\right)$ |



Space-Approximation Tradeoff

## Previous work

- Best known upper bound: $\tilde{O}\left(n^{2} / \alpha^{3}\right)$ bits ([AKLY16])
- Best known lower bound: $\Omega\left(n^{2} / \alpha^{3}\right)$ bits ([DK20])
- Gap of $\operatorname{polylog}(n)$ bits
- These types of polylog(n) gaps appear frequently in dynamic streams
- One key reason is a main technique for finding edges in a dynamic streams


## Previous work

$L_{0}$-Samplers:

- It is non-trivial to find even one edge in a dynamic stream
- $L_{0}$-Samplers are a key tool to solve this problem
- They can sample an edge uniformly at random from a set of pairs of vertices undergoing edge insertions and deletions


## Previous work

- $L_{0}$-Samplers can be implemented in $O\left(\log ^{3} n\right)$ bits of space [JST11]
- $\Omega\left(\log ^{3} n\right)$ bits are also necessary [Kap+17]
- Many problems in streaming have the polylog $(n)$ overhead because of the use of $L_{0}$-samplers
- Connectivity has a lower bound of $\Omega\left(n \log ^{3} n\right)([N Y 19])$


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This closes the gap up to constant factors
Some problems do not need the polylog( $n$ ) overhead
If $\alpha>n^{1 / 2}$ then there is not enough space to output the answer:

$$
\frac{n}{\alpha}>\frac{n^{2}}{\alpha^{3}}
$$

## Algorithm

# We will now show how to prove this! 

## Assumptions

Simplifying Assumptions for this talk:

- The input graph is bipartite
- The maximum matching has size $\Omega(n)$
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All these assumptions can be lifted!

## Hard Instances

A hard instance from previous work [Kon15, AKLY16, DK20]:


Lower Bound [DK20]: $\Omega\left(n^{2} / \alpha^{3}\right)$ bits

## Approach

(1) Match or Sparsify:

- Either find a large matching
- Or identify hard instances similar to hard instances of previous work
(2) Solve the hard instances

Note: We run these algorithms in parallel

## Match Or Sparsify

(1) Find a matching $M_{\text {easy }}$ in space $O\left(n^{2} / \alpha^{3}\right)$ bits such that:

- Either $\left|M_{\text {easy }}\right|=\Omega(n / \alpha)$



## Match Or Sparsify

(1) Find a matching $M_{\text {easy }}$ in space $O\left(n^{2} / \alpha^{3}\right)$ bits such that:

- Either $\left|M_{\text {easy }}\right|=\Omega(n / \alpha)$
- Or Subgraph induced on unmatched vertices has $\tilde{O}(n)$ edges and a matching of size $\Omega(n)$



## Match Or Sparsify

Idea:

- Sample $O\left(n^{2} / \alpha^{3} \operatorname{polylog}(n)\right)$ random edges
- $L_{0}$-samplers take space polylog $(n)$
- $M_{\text {easy }}$ is a greedy matching over the sampled edges
- Similar to residual greedy property of matching (used in [Ahn+18, Kon18])
- Different proof but along the same lines


## Similarity to Hard Instances

The instances we focus on are qualitatively same as the hard instances


## Solving Hard Instances



Analysis of [DK20]:

- We need $n^{2} / \alpha^{3}$ edges
- Space: $O\left(\left(n^{2} / \alpha^{3}\right) \cdot \log (n)\right)$ bits
- Lo-samplers: $O\left(\left(n^{2} / \alpha^{3}\right) \cdot \operatorname{polylog}(n)\right)$ bits


## Solving Hard Instances

We know the partition $U, B$ at the end of the stream from Match Or Sparsify step


B

## Grouping

Consider the bipartite graph

| $n$ | 0 | 0 | $n$ |
| :--- | :--- | :--- | :--- |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |

## Grouping

Partition left randomly into groups of size $\alpha$


## Grouping

$V_{i}$ lies within $B$ with probability $1-o(1)$


## Grouping

Focus on group $V_{i}$ that lies within $B$


## Grouping

$V_{i}$ has $\alpha$ edges to $B ; \quad$ We just need one edge;


## Grouping

$1 / \alpha$ fraction of vertices on right are in the neighborhood of $V_{i}$


## Grouping

$V_{i}$ has $n / \alpha$ vertices in its neighborhood


## Grouping

$o\left(n / \alpha^{2}\right)$ from $U ; \quad n / \alpha$ from $B$;


## Grouping

$V_{i}$ has just 1 edge in $B$


## Grouping

Can we find this one neighbor efficiently?


## Grouping

- This is like the set disjointness problem from communication complexity
- Need to find a vertex that has an edge from $V_{i}$ and is from $B$



## Recovery

Need to find a vertex that is from $B$ and also has an edge from $V_{i}$

- Trivial solution: $O\left(n \log n / \alpha^{2}\right)$ bits
- Goal: $O\left(n / \alpha^{2}+\log n\right)$ bits
- So $n / \alpha$ groups will imply space of $O\left(n^{2} / \alpha^{3}\right)$ bits

$o\left(n / \alpha^{2}\right)$
$n / \alpha$



## Recovery

Idea:

- Represent the neighborhood of $V_{i}$ as a binary vector
- Compute inner products with random vectors


## Recovery

Idea:

- Represent the neighborhood of $V_{i}$ as a binary vector
- Compute inner products with random vectors
- Recovery: Go over all possible neighbor vectors and check if the inner products match


## Recovery

Idea:

- Number of possible neighbor vectors: $2^{o\left(n / \alpha^{2}\right)} \cdot n$
- Space: $O\left(n / \alpha^{2}+\log n\right)$ bits


B

## Issues

- We can find the neighbor of $V_{i}$
- But we do not know the name of the endpoint in $V_{i}$
- Cannot recover an edge
- We need grouping on the right too



## Grouping

Consider the bipartite graph

| $n$ | 0 | 0 | $n$ |
| :--- | :--- | :--- | :--- |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |
| 0 | 0 |  |  |

## Grouping

Random grouping on both sides


## Grouping

$V_{i}$ lies within $B$ with probability $1-o(1)$


## Grouping

Focus on group $V_{i}$ that lies within $B$


## Grouping

$V_{i}$ has $\alpha$ edges to $B$; We just need one edge;


## Grouping

$1 / \alpha$ fraction of groups on right are in the neighborhood of $V_{i}$


## Grouping

$V_{i}$ has $n / \alpha^{2}$ groups in its neighborhood


## Grouping

The green groups lie completely within $B$


## Grouping

$V_{i}$ has an edge to $V_{j}$


## Recovery

- There may be multiple edges between $V_{i}$ and $V_{j}$
- But there is just one edge between them with high constant probability



## Grouping

Want to recover the edge between $V_{i}$ and $V_{j}$


## Recovery

- We know $u$ is a neighbor of $V_{i}$ (from Neighborhood sketch of $V_{i}$ )
- We know $v$ is a neighbor of $V_{j}$ (from Neighborhood sketch of $V_{j}$ )
- Thus, $(u, v)$ must be an edge



## Challenges

We need to solve a more general problem


## Challenges

## Challenges:

- $\tilde{O}(n)$ edges
- Cannot bound the degree of vertices with a constant



## Sparse Neighborhood Recovery

- $G=(V, E)$ specified in a dynamic stream
- $S \subseteq V$ known before the stream
- $T \subseteq V$ revealed after the stream
- Goal: Return $N(S)-T$



## Sparse Neighborhood Recovery

## Promises:

(1) $|T| \leq a$;
(2) $|N(S)-T| \leq b$;
(3) for every vertex $v \in N(S)-T,|S \cap N(v)|=O(1)$


## Sparse Neighborhood Recovery

## Space:

(1) Trivial solution: $O(a \log n+b \log n)$ bits
(2) Goal: $O(a+b \log n)$ bits


## Sparse Neighborhood Recovery

Solution:
(1) We can solve the problem using previous ideas of inner products
(2) Problems:

- Exponential time for recovery
- Random bits needed is much more than space budget


## Sparse Neighborhood Recovery

Solution:
(1) We can solve the problem using previous ideas of inner products
(2) Problems:

- Exponential time for recovery
- Random bits needed is much more than space budget
(3) Solution using ideas from sparse recovery (complicated)
(9) Space bound: $O(a+b \log n)$ bits
(5) This bound is information-theoretically optimal


## Solving General Hard Instance

- Using sparse neighborhood recovery sketch we can solve the general hard instance
- Space: $O\left(n^{2} / \alpha^{3}\right)$ bits



## Summary

## Concluding Remarks

## Summary

(1) Match or Sparsify: In $O\left(n^{2} / \alpha^{3}\right)$ bits of space

- We either get a large matching
- Or get a hard instance that is sparse and contains a large matching
(2) Our sparse recovery sketches can be used to solve these hard instances in $O\left(n^{2} / \alpha^{3}\right)$ bits
(3) We run both algorithms in parallel and get the final algorithm


## Summary

- There is a dynamic streaming algorithm that whp outputs an $\alpha$-approximation to maximum matching using $O\left(n^{2} / \alpha^{3}\right)$ bits of space


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## Summary

- There is a dynamic streaming algorithm that whp outputs an $\alpha$-approximation to maximum matching using $O\left(n^{2} / \alpha^{3}\right)$ bits of space
- The lower bound of [DK20] is $\Omega\left(n^{2} / \alpha^{3}\right)$ bits making our algorithm optimal
- polylog(n) overhead of $L_{0}$-samplers is not always necessary (Unlike [NY19])


## Open Problems

- These polylog(n) overheads due to use of $L_{0}$-samplers are prevalent in dynamic stream literature
- Can our techniques be used to bypass polylog(n) overheads for other problems:
- E.g. Vertex Cover, Dominating Set, Vertex Connectivity


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Thank you!

