

# Survey on Matching in the Graph-Stream Model

CS328 Project

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# Introduction

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# Rise of Big Data

- In the last few decades, the world has witnessed exponential growth in the number and size of real world data.
- Analysing these massive data using classical algorithms is a challenging task.
- Two approaches to analyze such massive data:
  - Data Streaming
  - Distributed Processing

# Graph Streaming

- Streaming algorithms sequentially scans the input data.
- Input data streams can be in random order or in adversarial order.
- Specifically, in graph streaming the input stream is of vertices or edges.
- Streaming algorithm uses  $\mathcal{O}(\text{poly log } n)$  (polylogarithmic) memory.

# Semi-Streaming Model

- Polylogarithmic memory is insufficient for many graph problems [3].
- Even the basic bipartiteness or connectivity problems in graphs requires  $\Omega(n)$  space.
- Semi-Streaming Model: Allow  $\mathcal{O}(npoly \log n)$  (or  $\tilde{\mathcal{O}}(n)$ ) space [2, 8].

# Maximum Matching

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# Maximum Matching Problem

## Maximum Cardinality Matching

Given a graph  $G = (V, E)$ , find a subset  $M \subseteq E$  of maximum size such that no two adjacent edges are selected.

- Simply called the (Unweighted) Maximum Matching Problem.
- **Maximum Bipartite Matching:** Maximum Matching problem on Bipartite Graphs

# Known Results and Bounds

- Fastest Algorithm:  $\mathcal{O}(m\sqrt{n})$  [7]
- Semi-Streaming Model:
  - Greedy Algorithm: 1/2 approximation
  - Hardness:  $1 - 1/e$  approximation [4]
  - Better than 1/2? Open Problem



# **Algorithms with Multiple Passes or Random Stream Orders**

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# Existing Semi-Streaming Algorithms

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- Multiple passes of stream
- Random Stream Orders

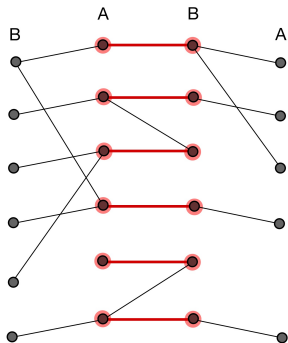
# Existing Semi-Streaming Algorithms

- Multiple passes of stream
- Random Stream Orders
- Standard Approach: Finding Augmenting Paths
- McGregor[6]:  $1/(1 + \epsilon)$  approximation with constant number of passes (strongly dependent on  $\epsilon$ )
- Feigenbaum et. al. [2]:  $2/3 - \epsilon$  approximation with  $\mathcal{O}(\log \frac{1}{\epsilon}/\epsilon)$  passes.

# Three Pass Algorithm on Arbitrary Stream Orders

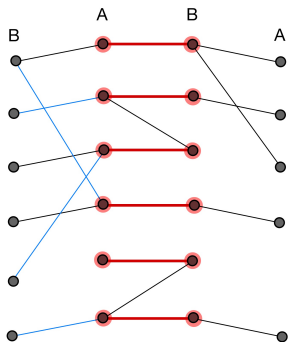
- **Idea:**
  - Compute a maximal matching  $M_G$  in one pass.
  - Utilize the second and third passes to find 3-augmenting paths.
  - Existence of 3-augmenting paths?
- **Lemma:** When Greedy is close to 1/2 approximation, there exists many 3-augmenting paths.[5]

# Three Pass Algorithm on Arbitrary Stream Orders



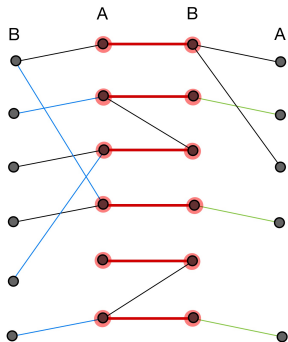
- **First Pass:**  
Compute a maximal matching  $M_G$

# Three Pass Algorithm on Arbitrary Stream Orders



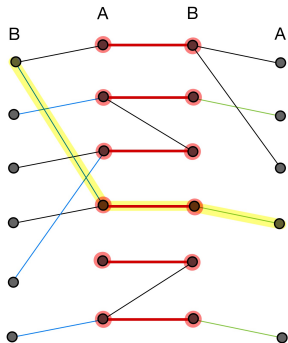
- **Second Pass:**  
Compute a maximal matching  $M_L$  between  $\overline{A(M_G)}$  and  $B(M_G)$

# Three Pass Algorithm on Arbitrary Stream Orders



- **Third Pass:**  
Compute a maximal matching  $M_R$  between  $\overline{B(M_G)}$  and  $\{a \in A(M_G) : M_G(a) \in B(M_L)\}$

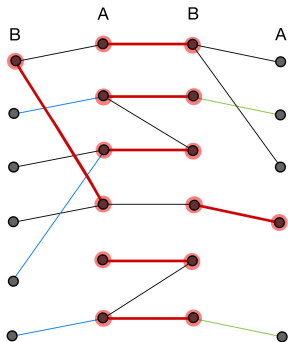
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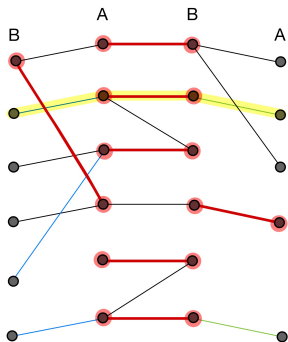
matching  $M_R$

between  $\overline{B(M_G)}$

and  $\{a \in A(M_G) :$

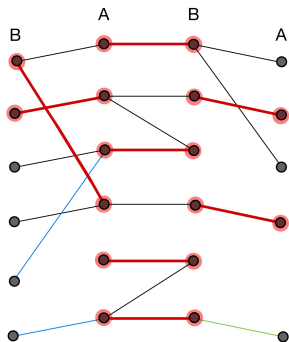
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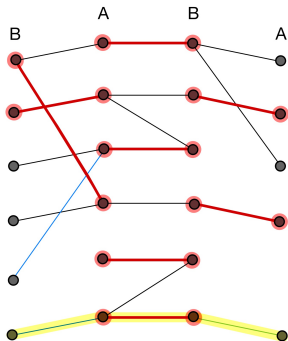
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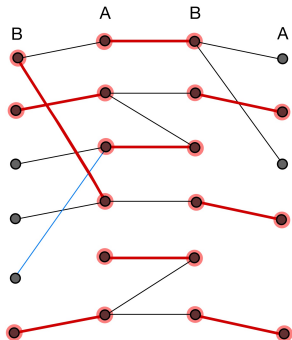
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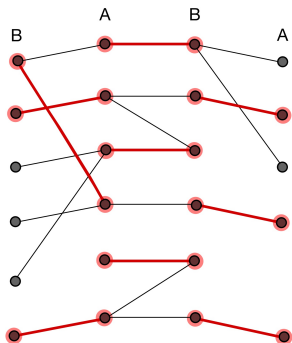
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# One-Pass Algorithm on Random Stream Orders

- **Lemma:** In expectation over all input edge sequences, if matching computed by Greedy algorithm is close to a  $1/2$  approximation, then Greedy builds this matching early on, in other words, converges quickly [5].

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- **Idea:**
  - Split the input stream into 3 phases.
  - First Phase: Compute a greedy matching  $M_0$ .
  - Second and Third Phases: Find 3-augmenting paths.
  - Also, compute greedy matching  $M_G$  in parallel.
  - Maximum of  $M_G$  and augmented  $M_0$  (with  $M_1 \cup M_2$ ).



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- 0.505 approximation, 0.503 approximation (General Graphs)

# Empirical Results

**Table 1:** Datasets Used (From SuiteSparse Matrix Collection)

<b>Dataset</b>	<b>Nodes</b>	<b>Edges</b>	<b>MBM</b>
IMDB	1,324,748	3,782,463	250,516
NotreDameActors	520,223	1,470,404	114,762

# Empirical Results

**Table 1:** Results Obtained (Average over 10 shuffles)


<b>Opt.</b>	<b>Gdy. &amp; 1 P</b>	<b>2 P(R)</b>	<b>2 P(D)</b>	<b>3 P</b>
250,516	215,997.6	227,317	238,831.2	240,097.6
114,762	97,293.2	100,744.5	106,448.6	108,300.5

# What is covered in our Survey?

- Focused on Maximum Cardinality Matching problem.
- Discussed bounds and hardness briefly.
- Surveyed algorithms dealing with multiple passes on arbitrary stream orders.
- Also Surveyed algorithms dealing with random stream orders (single and multiple passes).
- Have described the techniques presented in [6, 5, 1] in detail


# Future Work

- Survey techniques from results on more specific cases: Planar graphs, low-arboricity graphs, etc.
- Survey results on Weighted Matching.
- Parameterized Perspective analysis.
- Dynamic Graph streams.
- Results from Online Matching.
- Techniques from algorithms from other Graph problems in the streaming model (A general survey on Graph Streaming Algorithms.)

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