CPSC 768: Scalable and Private Graph Algorithms

Lecture 1: Intro

Quanquan C. Liu
quanquan.liu@yale.edu

“Practical” Algorithms

Heuristics

“Practical” Algorithms

Heuristics

Engineering

“Practical” Algorithms

Heuristics

Engineering

Math Tools

"Practical" Algorithms

Heuristics

Engineering

Tools from ML

Math Tools

“Practical” Algorithms

Heuristics

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Tools from ML

Math Tools

“Practical” Algorithms

Provably efficient algorithms

Models that **consider modern challenges** and **computing environments**

Goal: **Data structures** with best theoretical guarantees

Implementable in practice

Key Modern Challenge: **Massive** Datasets

MASSIVE graph data sets

ClueWeb

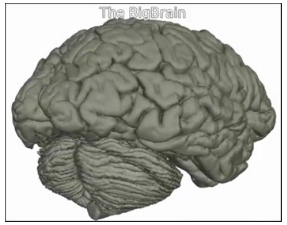
Google

~ 27 billion comments

~ 10 billion edges

~ 6 trillion edges

Web Data Commons Hyperlink Graph



~ 128 billion hyperlinks

~ 2 billion follows

~ 300 million neurons

Main Takeaway of the Class

- This class is focused on **research**
  - Use the **techniques you learn** outside of this class
  - Start **conducting research in these topics** and **more**
  - Exposure to practice problems and **open problems**
  - **Complete a final project**

Logistics

- Course website: https://quanquancliu.com/cpsc768
  - Everything important!
  - Syllabus
  - Recommended topics
  - Class schedule
  - Links to a bunch of papers
  - Class notes (posted as a batch for the week on Sunday)
- **Open problem session scheduling** + survey: https://forms.gle/CsKnH5DvuVu5XKXQA

Format and Workload

- **Two class presentations** on subjects of their choice related to the topics of the course. *50% of grade.*
  - Finalize dates and topics for presentations before **April 1: due Feb. 5**.
  - Finalize dates and topics for presentations on and **after April 1: due Feb. 26**.
- **One final project** (individual or with partner). *50% of grade.*

Format and Workload

- **One final project** (individual or with partner). *50% of grade.*
  - *Project proposal (1 page): due Feb. 26.*
  - *Progress report (2-3 pages): due March 27.*
  - *In-class presentation: last two weeks of class.*
  - *Final report (at least 8 pages, less than 20): April 24*

Final Project Details (in the context of SODA/SOSA/ALENEX)

- **Reading project (e.g. SOSA paper):**
  - Read 2-3 papers on the same project and survey on key ideas
  - Service to the community for hard to read papers!

Final Project Details (in the context of SODA/SOSA/ALENEX)

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  - Make an improvement over previous result
  - Solve an open problem

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- **Reading project (e.g. SOSA paper):**
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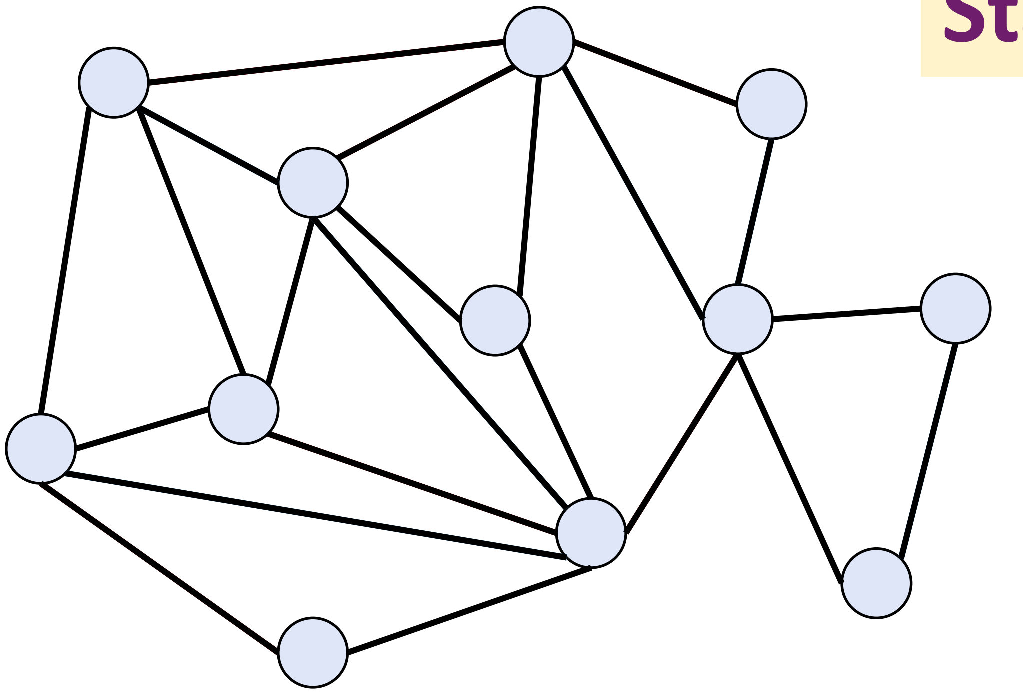
  - Service to the community for hard to read papers!
- **Theory project (e.g. SODA paper):**
  - Make an improvement over previous result
  - Solve an open problem
- **Implementation project (e.g. ALENEX paper):**
  - Algorithm engineering implementation of an algorithm
  - Give a *more implementable* solution with same or better theory guarantees
- More details given in the syllabus

A Brief Overview of Some Models Covered in This Class

A Key Focus on Graphs



Static or Dynamic

A Brief Overview of Models We'll Cover

How to represent graph:
• On one machine • Distributed across many machines

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How to represent graph:	What resources to process:
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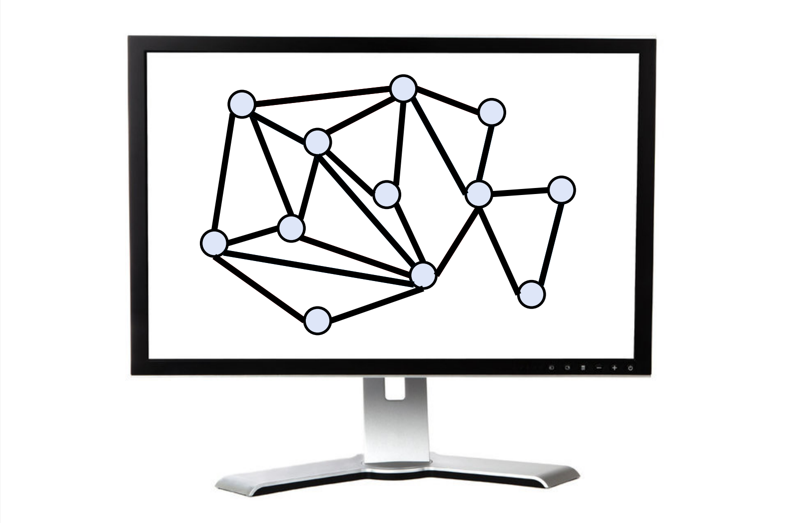
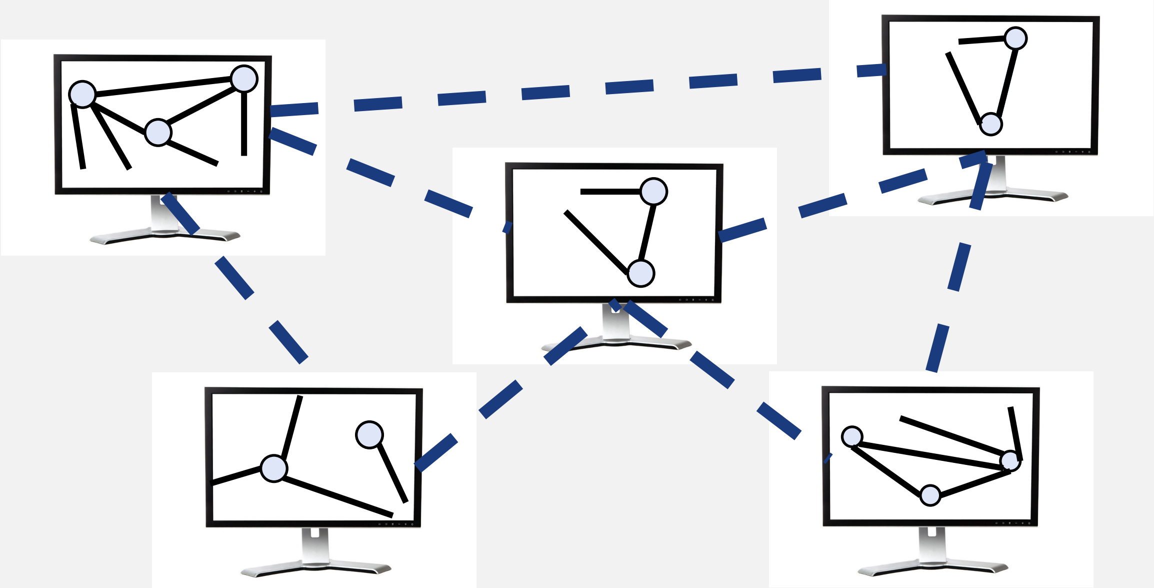
A Brief Overview of Models We'll Cover

How to represent graph:	What resources to process:
• On one machine • Distributed across many machines	• Multiple cores • Communication network over machines
How updates are given:	**Adversarial models:**
• In batches of multiple updates • As a stream of updates	• Adaptive/oblivious • Privacy violating • Central/Local

How to Represent the Graph

- On one machine
- Distributed across many machines





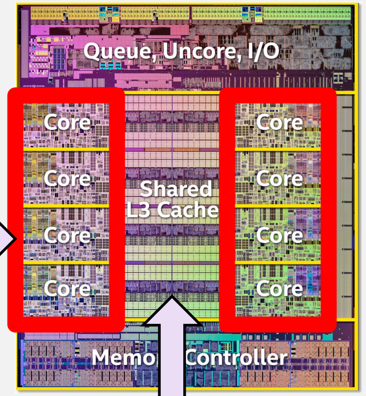
What Resources to Use to Process Graph

- Multiple cores and processors
- Communication network over machines

What Resources to Use to Process Graph

- **Multiple cores and processors**
- Communication network over machines

Cores: parallel processing



Shared-memory: read and write from same memory

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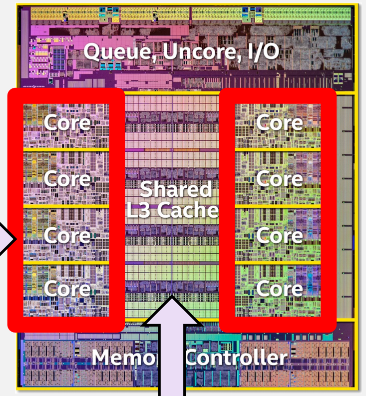

Shared-memory: read and write from same memory

Shared-memory work-depth model

- **Work:**
  - Total number of operations
- **Depth/Span:**
  - Longest chain of sequential dependencies in algorithm

What Resources to Use to Process Graph

- Multiple cores and processors
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Massively Parallel Computation (MPC) Model

- M machines
- Synchronous rounds

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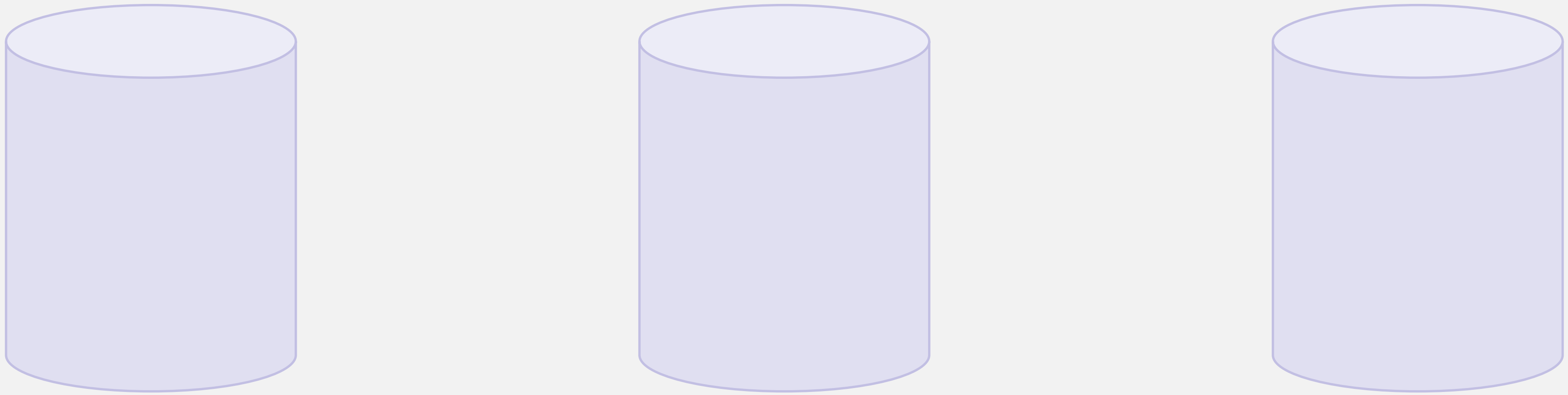

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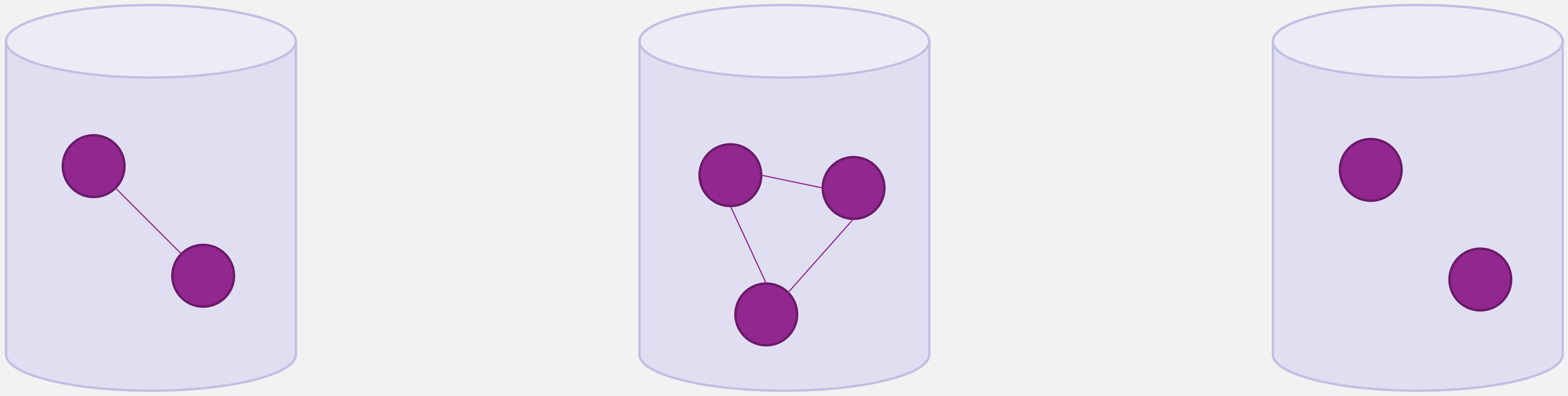

What Resources to Use to Process Graph

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Massively Parallel Computation (MPC) Model

- M machines
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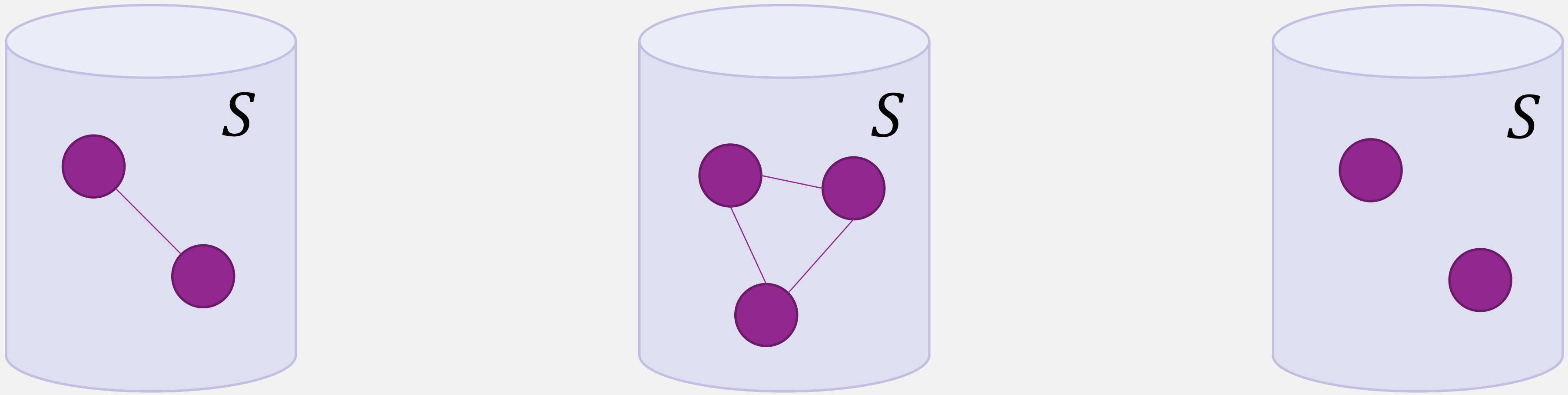
- S space per machine



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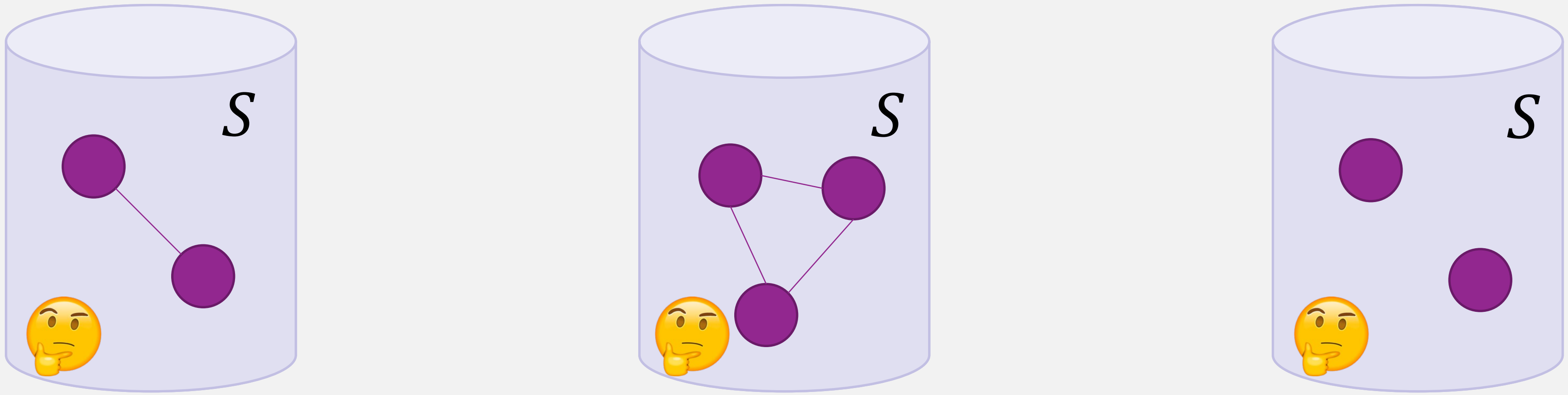

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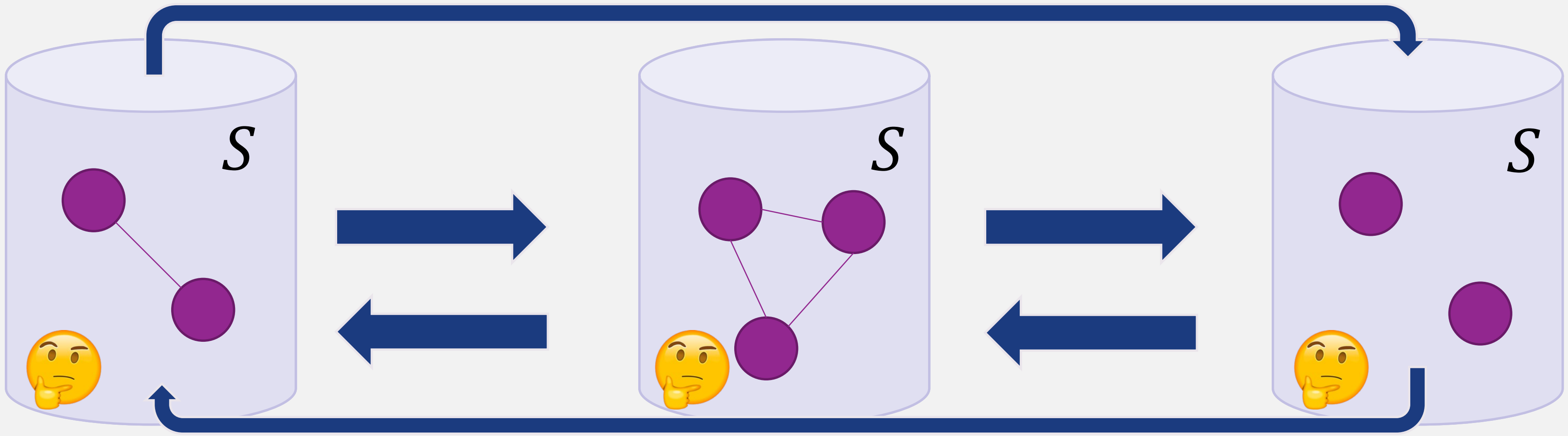

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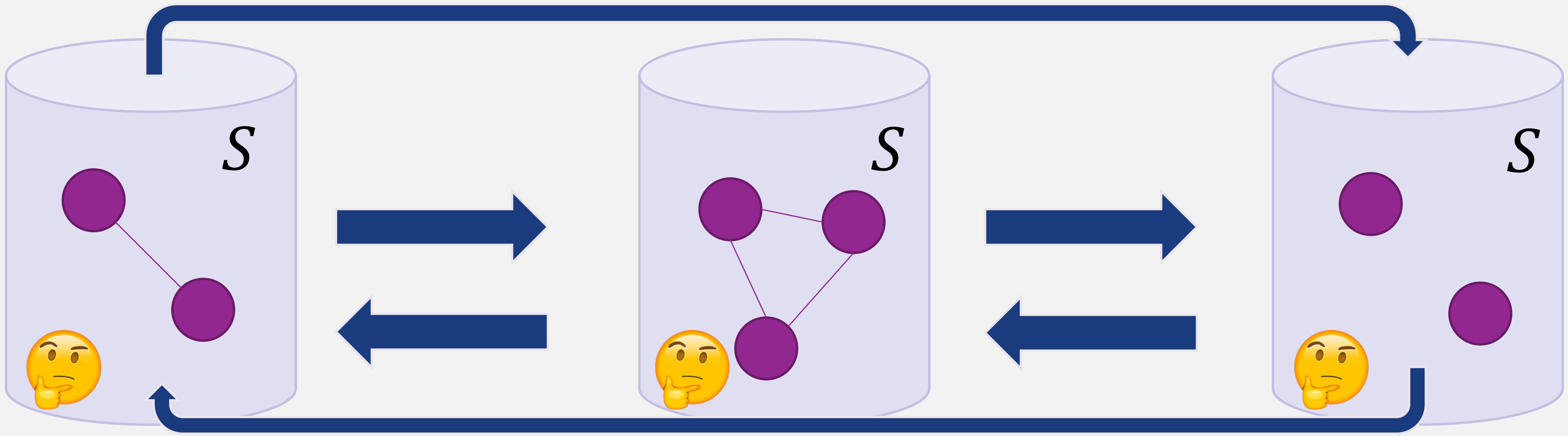
Total Space: $\boldsymbol{M \cdot S}$



What Resources to Use to Process Graph

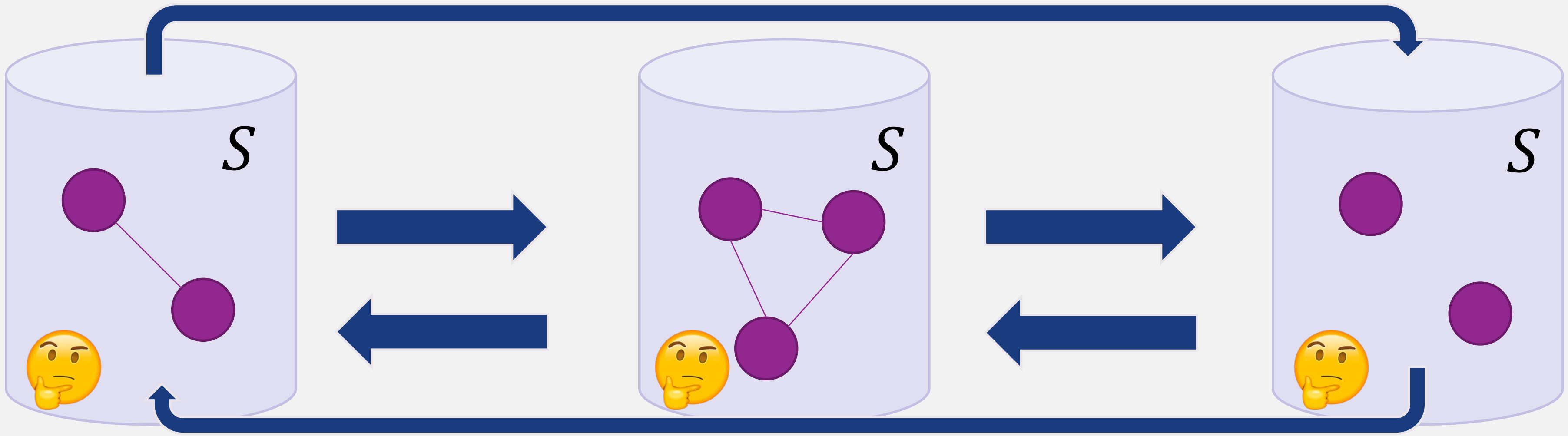
- Multiple cores and processors
- **Communication network over machines**

Complexity measures:
- **Total Space**
- **Space Per Machine**
- **Rounds of communication**

Massively Parallel Computation (MPC) Model

- *M* machines
- Synchronous rounds
- *S* space per machine

Total Space: $\boldsymbol{M \cdot S}$

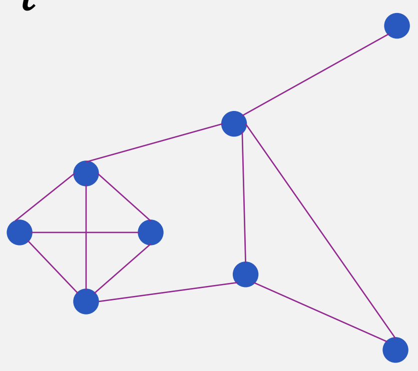


How Updates are Given

- **In batches of multiple updates**
- As a stream of updates

Batch-dynamic model

G_i



Old Graph

How Updates are Given

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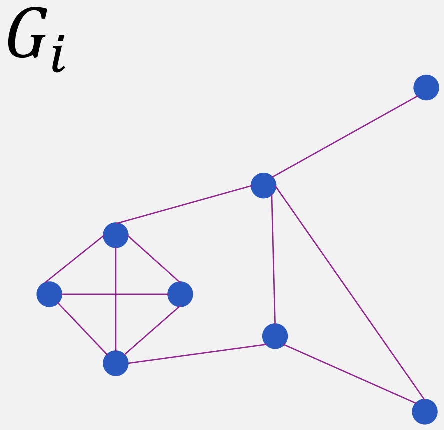
Batch-dynamic model



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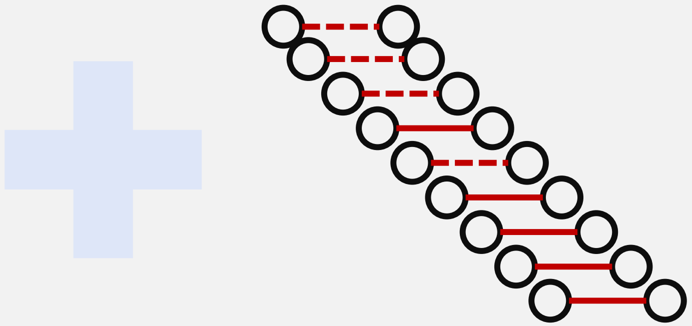

Batch of Updates

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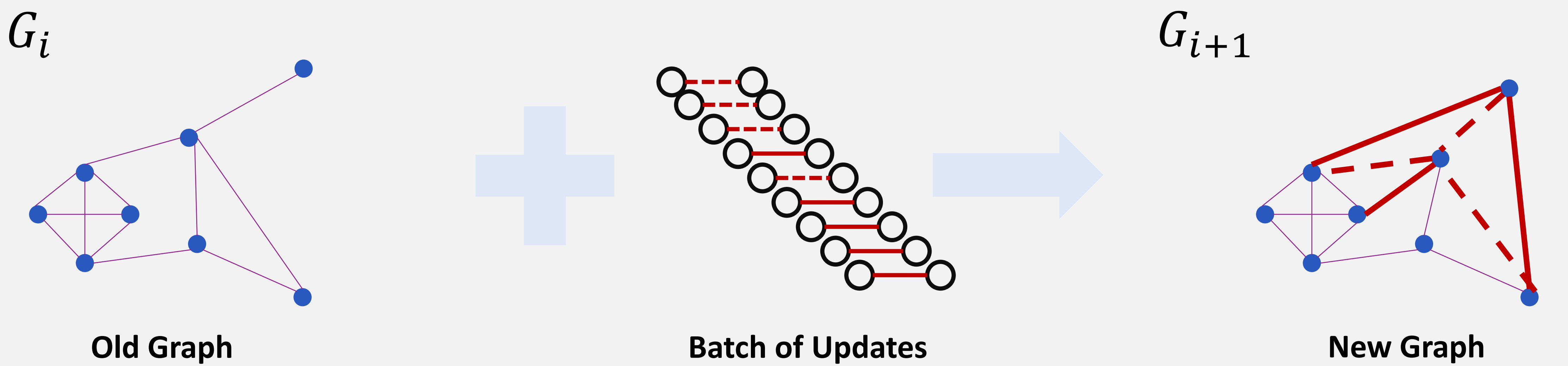

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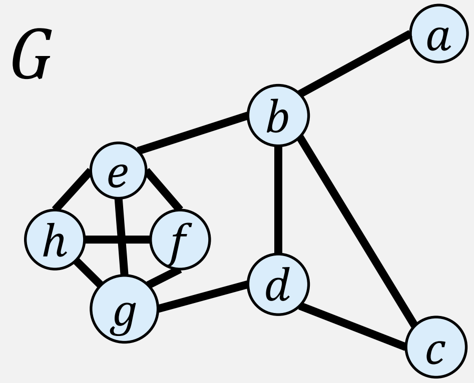
Streaming Model



Input Graph

How Updates are Given

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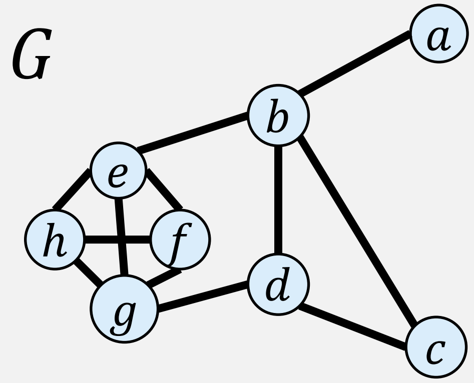

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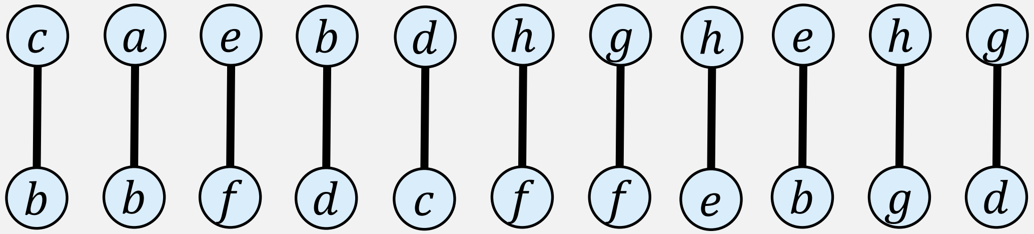

Input Stream

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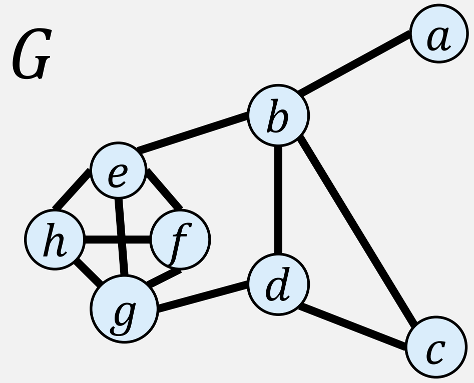

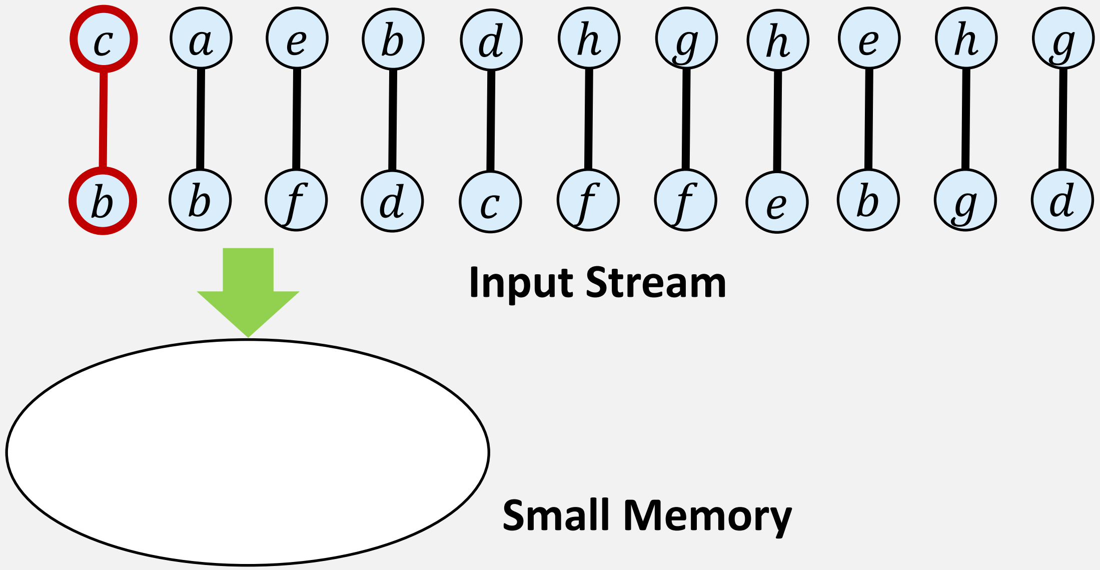

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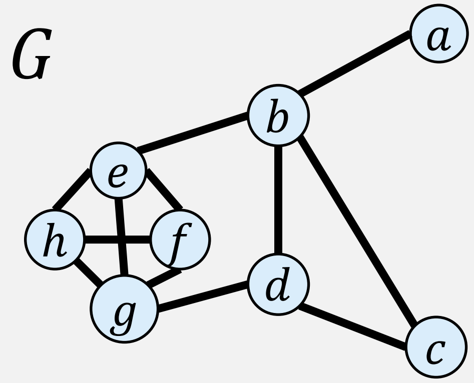

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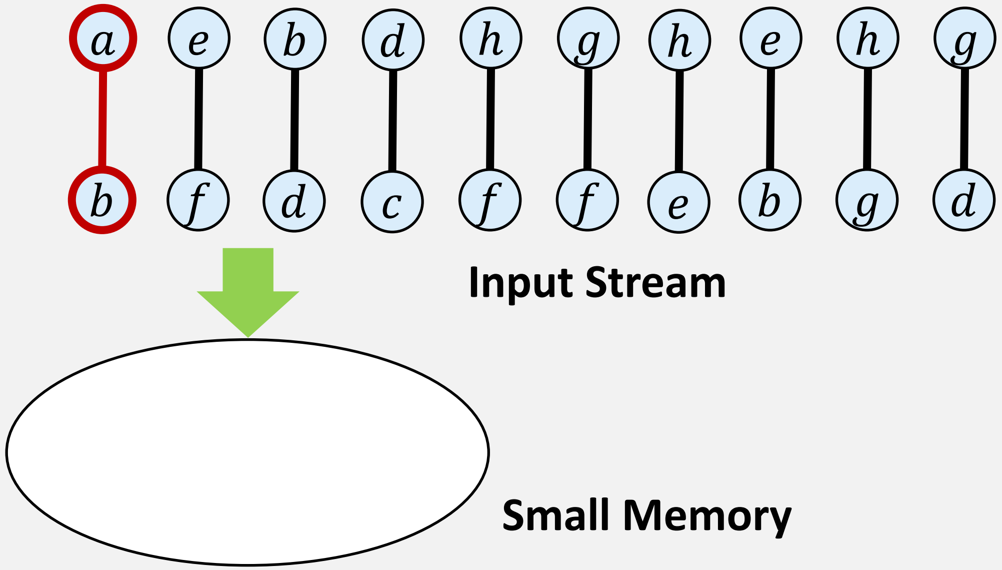

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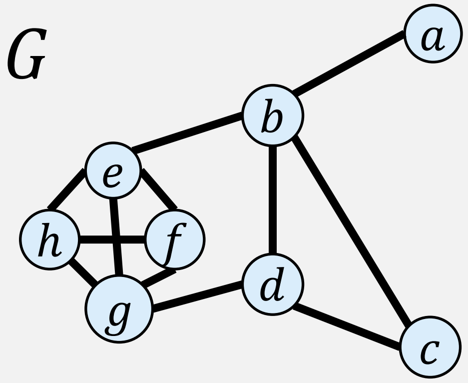

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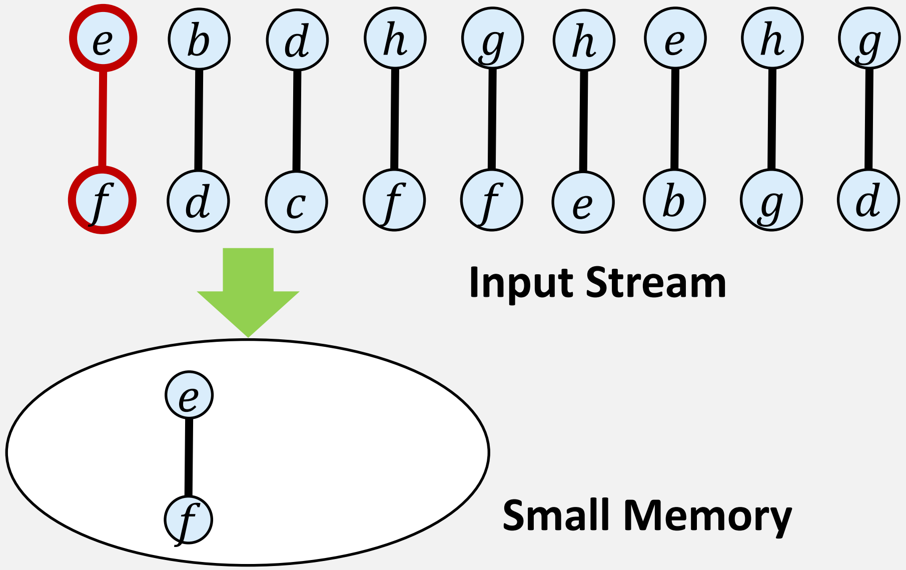

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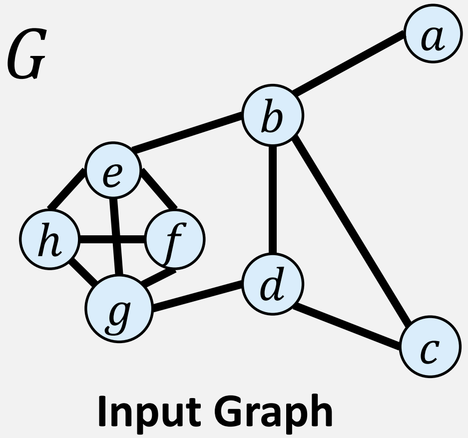

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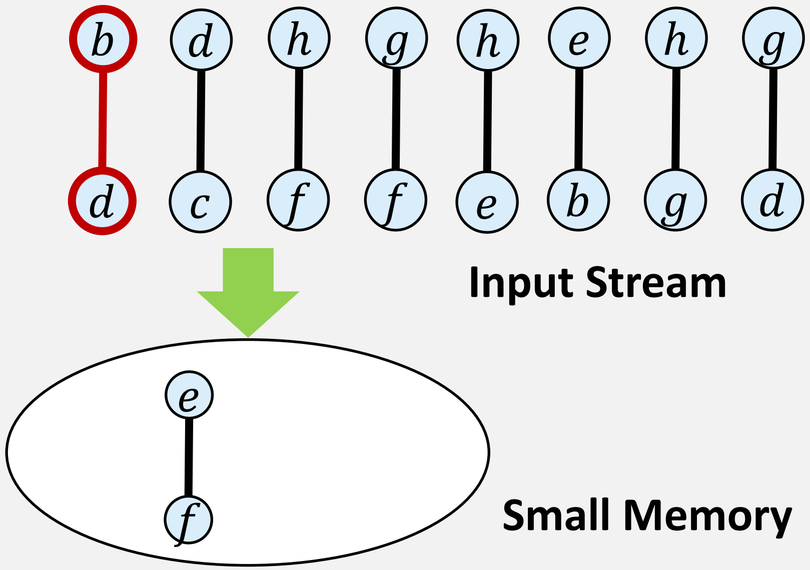

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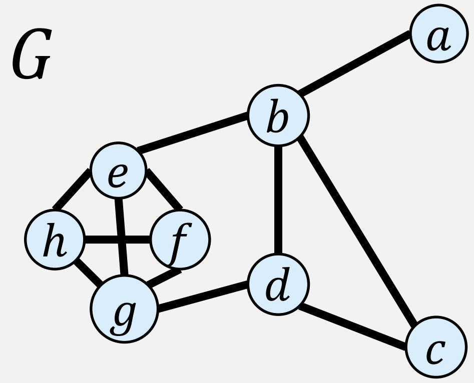

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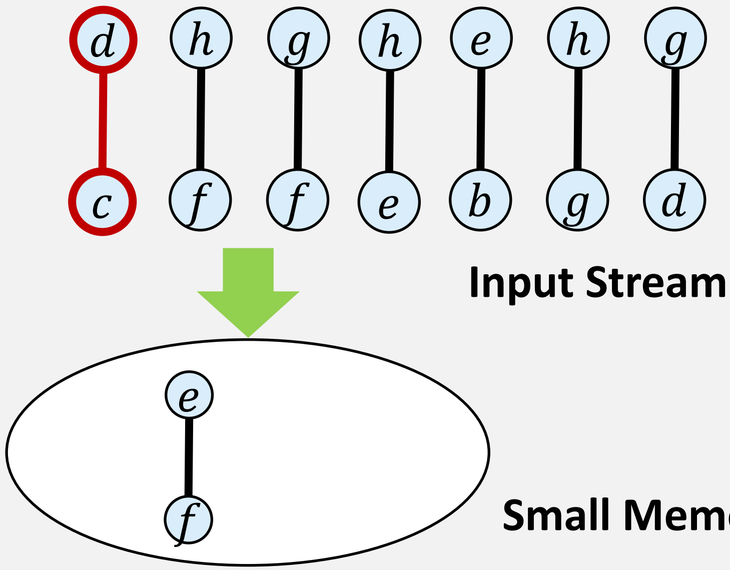

Input Stream

Small Memory

How Updates are Given

- In batches of multiple updates
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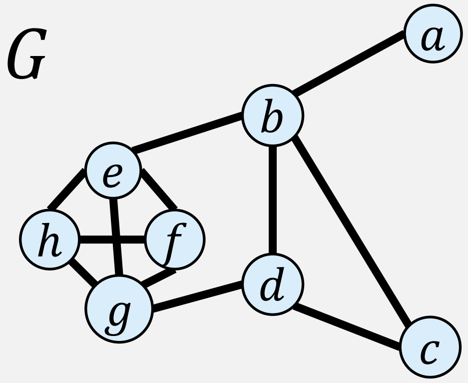
Streaming Model



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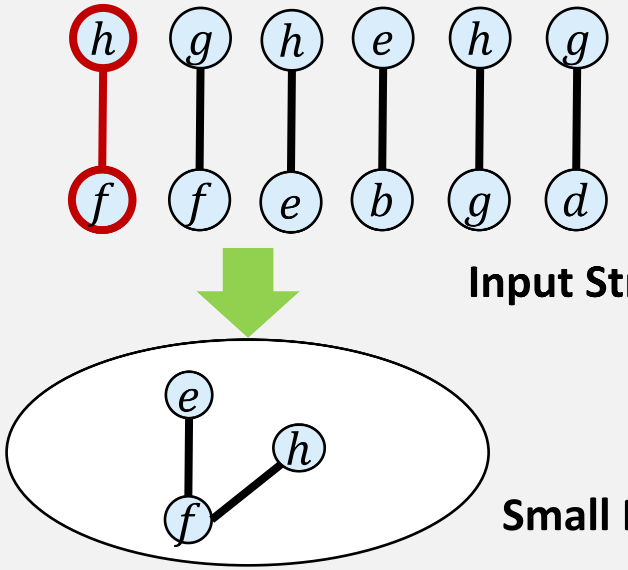

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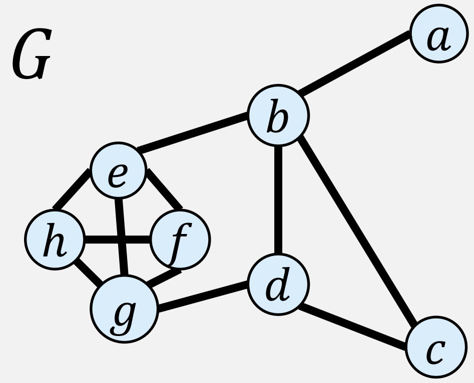

Input Graph

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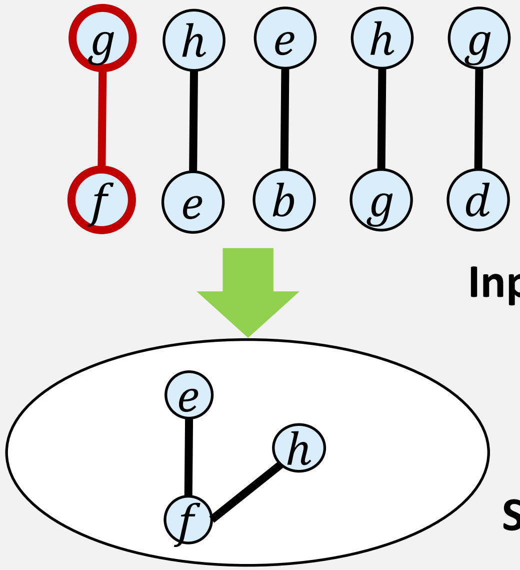

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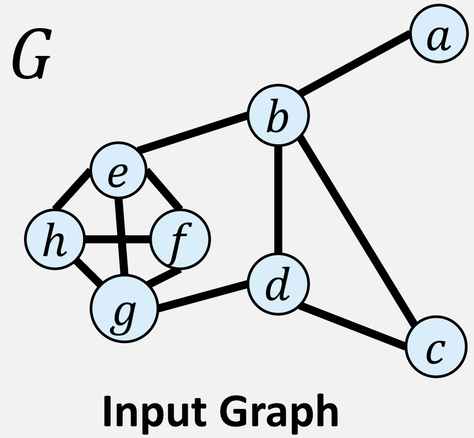

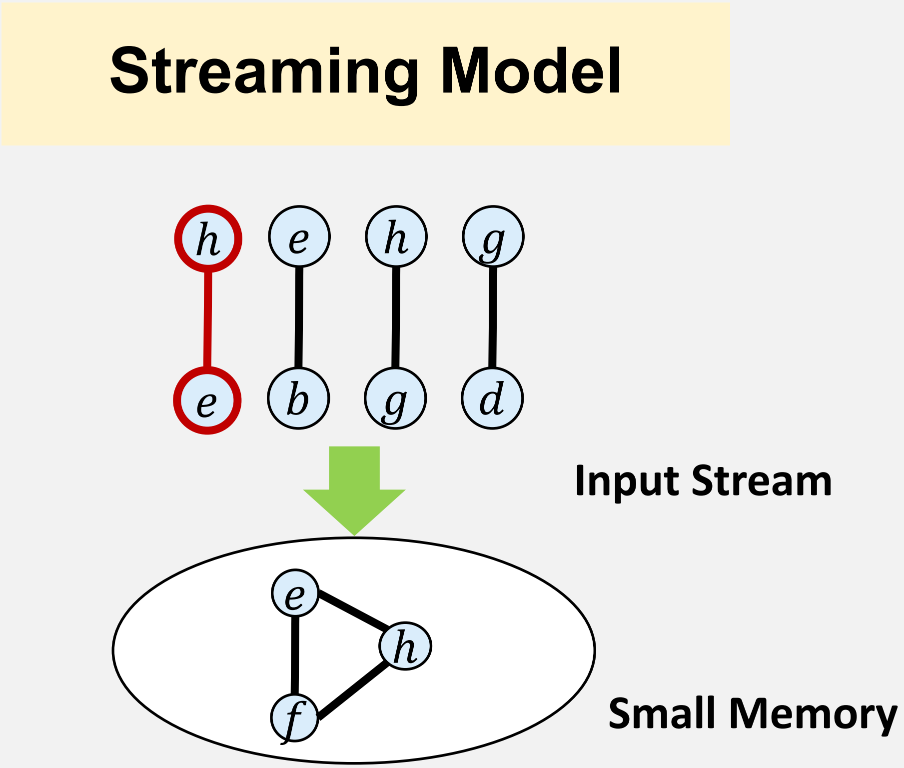

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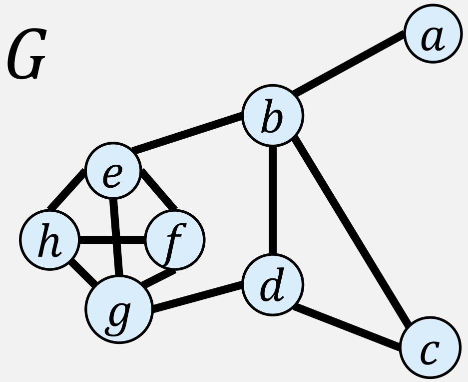
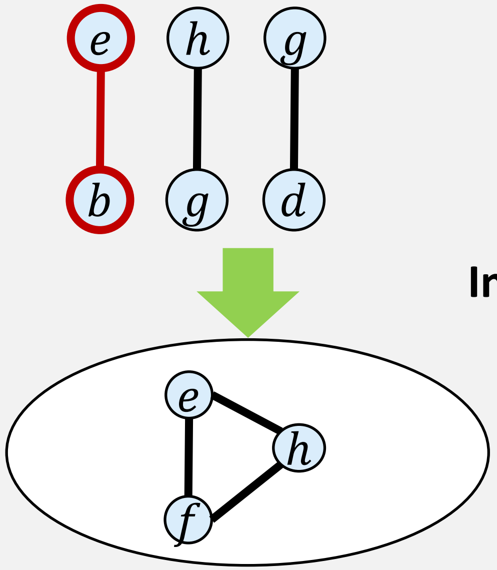


Input Graph

Streaming Model



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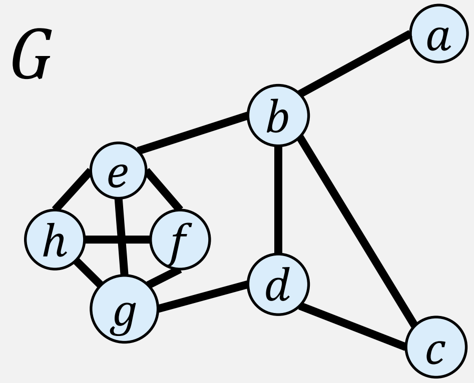

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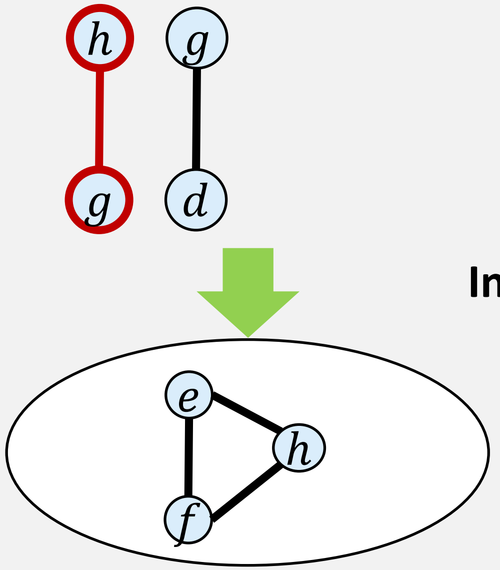

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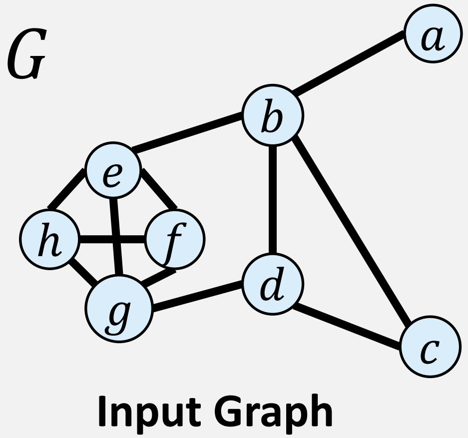

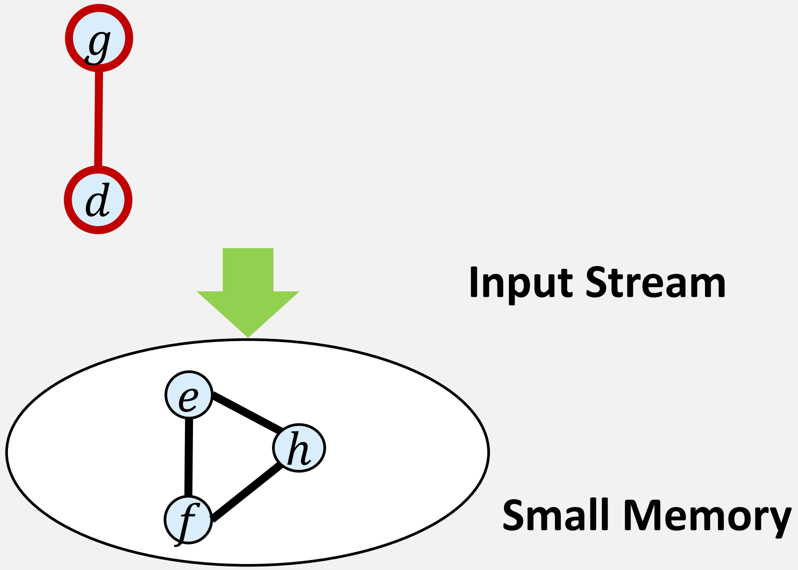

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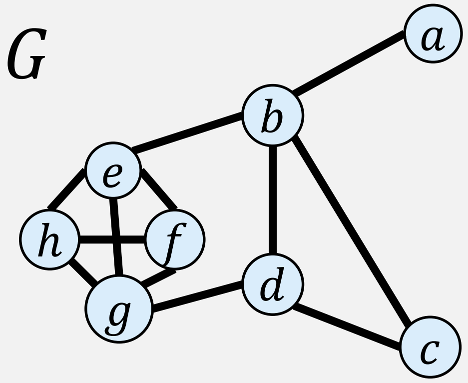
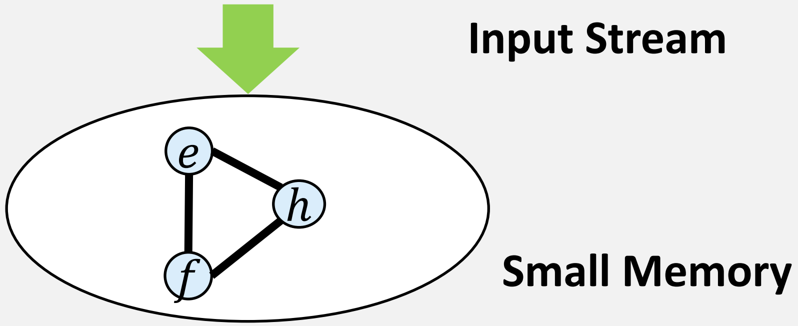


Input Graph

Complexity measures:
- Memory size
- Number of passes



Adversarial Models

- Adaptive/oblivious
- Privacy violating

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Oblivious: no knowledge on algorithm outputs
Adaptive: can see previous algorithm outputs
(sometimes internal random bits)

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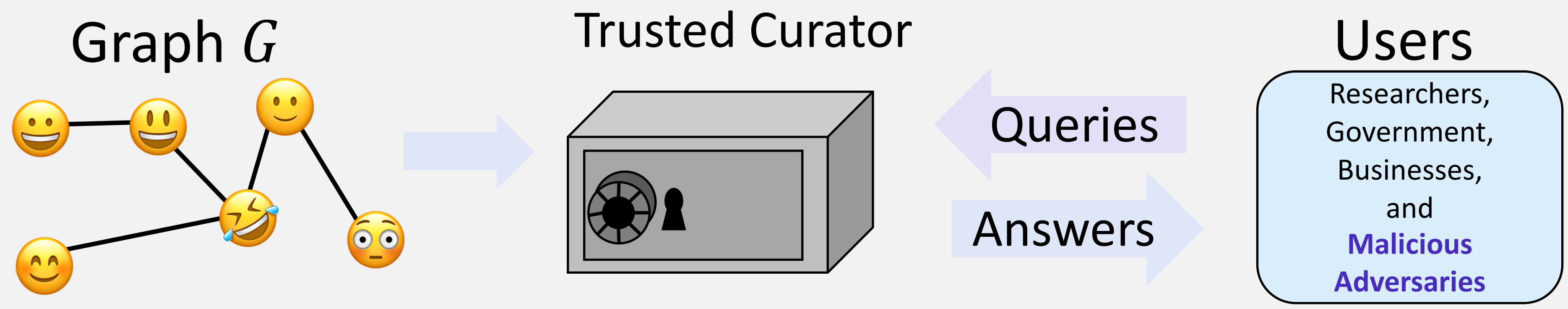
Differential Privacy: Central Model (DP)



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Oblivious: no knowledge on algorithm outputs
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Differential Privacy: Central Model (DP)

Differential Privacy

An algorithm $\mathcal{A}$ is **ε-differentially private** if for all pairs of neighbors G and G' and all sets of possible outputs S:

$$\Pr[\mathcal{A}(G) \in S] \leq e^{\varepsilon} \cdot \Pr[\mathcal{A}(G') \in S].$$

Neighboring inputs differ in some information we'd like to hide

Adversarial Models

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- **Privacy violating**

Oblivious: no knowledge on algorithm outputs
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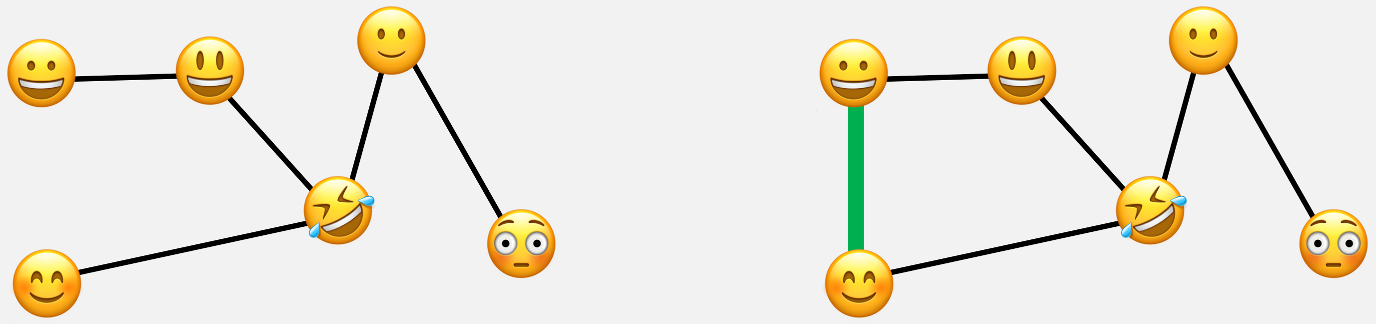
Neighboring Inputs



Edge-neighboring graphs: differ in **one edge**

Adversarial Models

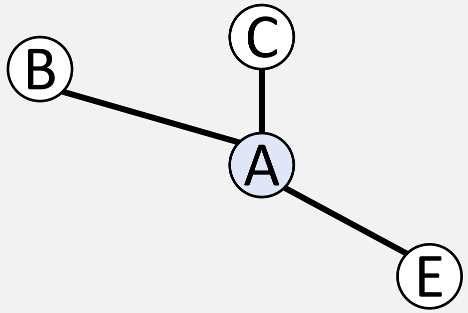
- Adaptive/oblivious
- **Privacy violating**

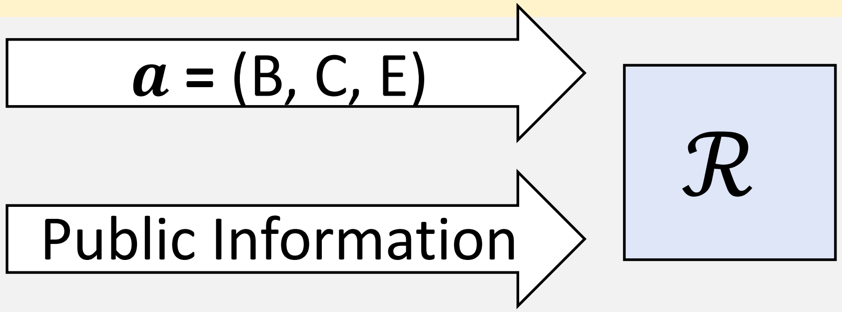
Oblivious: no knowledge on algorithm outputs
Adaptive: can see previous algorithm outputs (sometimes internal random bits)

Differential Privacy: Local Model (LDP)

Local Randomizer

An **ε-local randomizer** $\mathcal{R}$ is an ε-differentially private algorithm that takes as input an adjacency list $\boldsymbol{a}$ and public information.





Combinations of Models

Batch-Dynamic + {**Shared-memory work-depth, MPC**}

Combinations of Models

Batch-Dynamic + {**Shared-memory work-depth, MPC**}

Dynamic + **Differential Privacy** = **Continual Release**

Combinations of Models

Batch-Dynamic + {**Shared-memory work-depth, MPC**}

Dynamic + **Differential Privacy** = **Continual Release**

Distributed + **Differential Privacy** = **Local Model**

Combinations of Models

Batch-Dynamic + {Shared-memory work-depth, MPC}

Dynamic + Differential Privacy = Continual Release

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Incremental/Fully Dynamic + Streaming

Combinations of Models

Batch-Dynamic + {**Shared-memory work-depth, MPC**}

Dynamic + **Differential Privacy** = **Continual Release**

Distributed + **Differential Privacy** = **Local Model**

Incremental/Fully Dynamic + **Streaming**

And many more…

Combinations of Models

Each model is great for a **different** real-world system!
But there are many!

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What problems can we study where solutions can be implemented in many models without many changes?