ProbGraph: High-Performance and High-Accuracy Graph Mining with Probabilistic Set Representations

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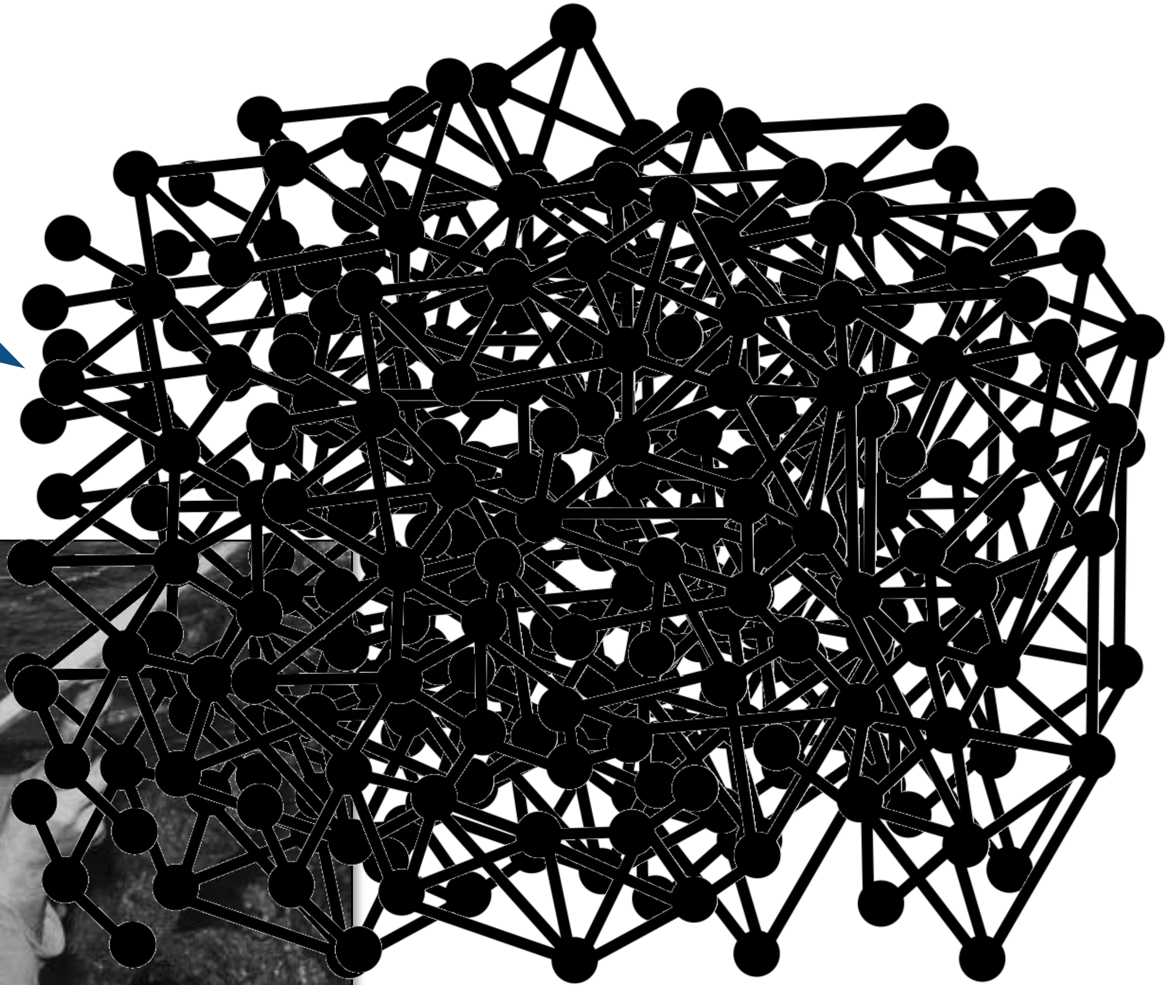
SC22 Dallas, TX | hpc accelerates.

Graph Mining

Graph Mining

A huge & complex graph dataset



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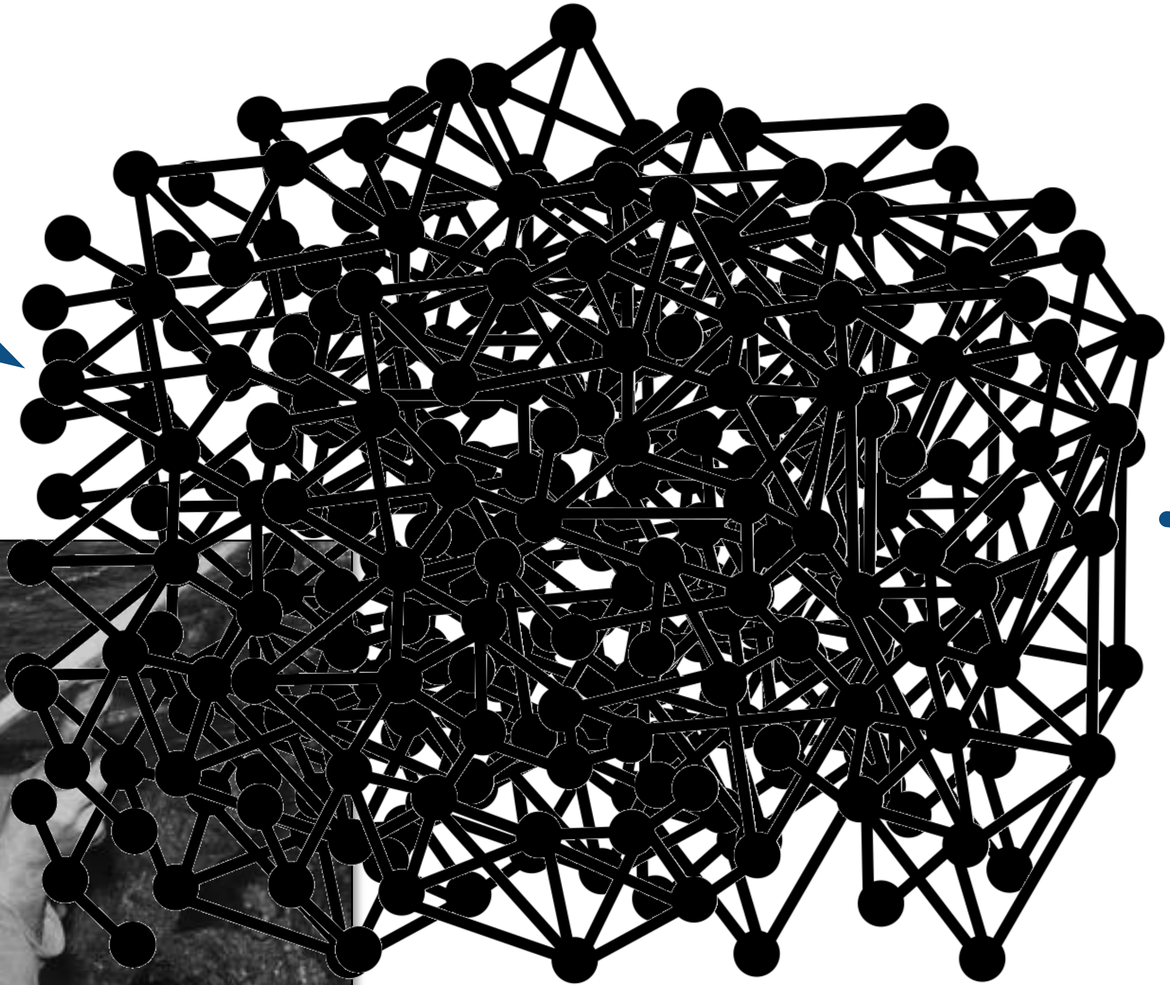
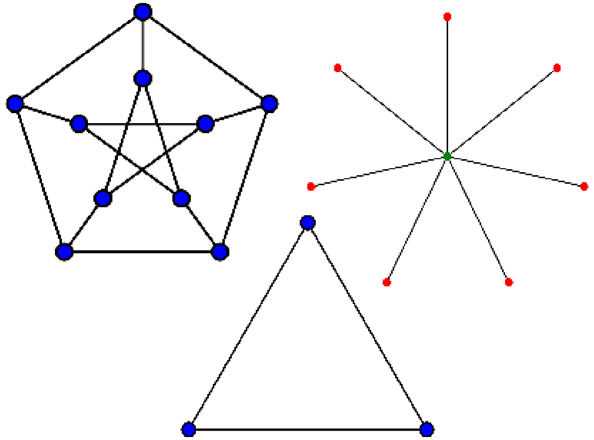


Pattern counting (triangles, higher-order cliques, dense subgraphs, ...)



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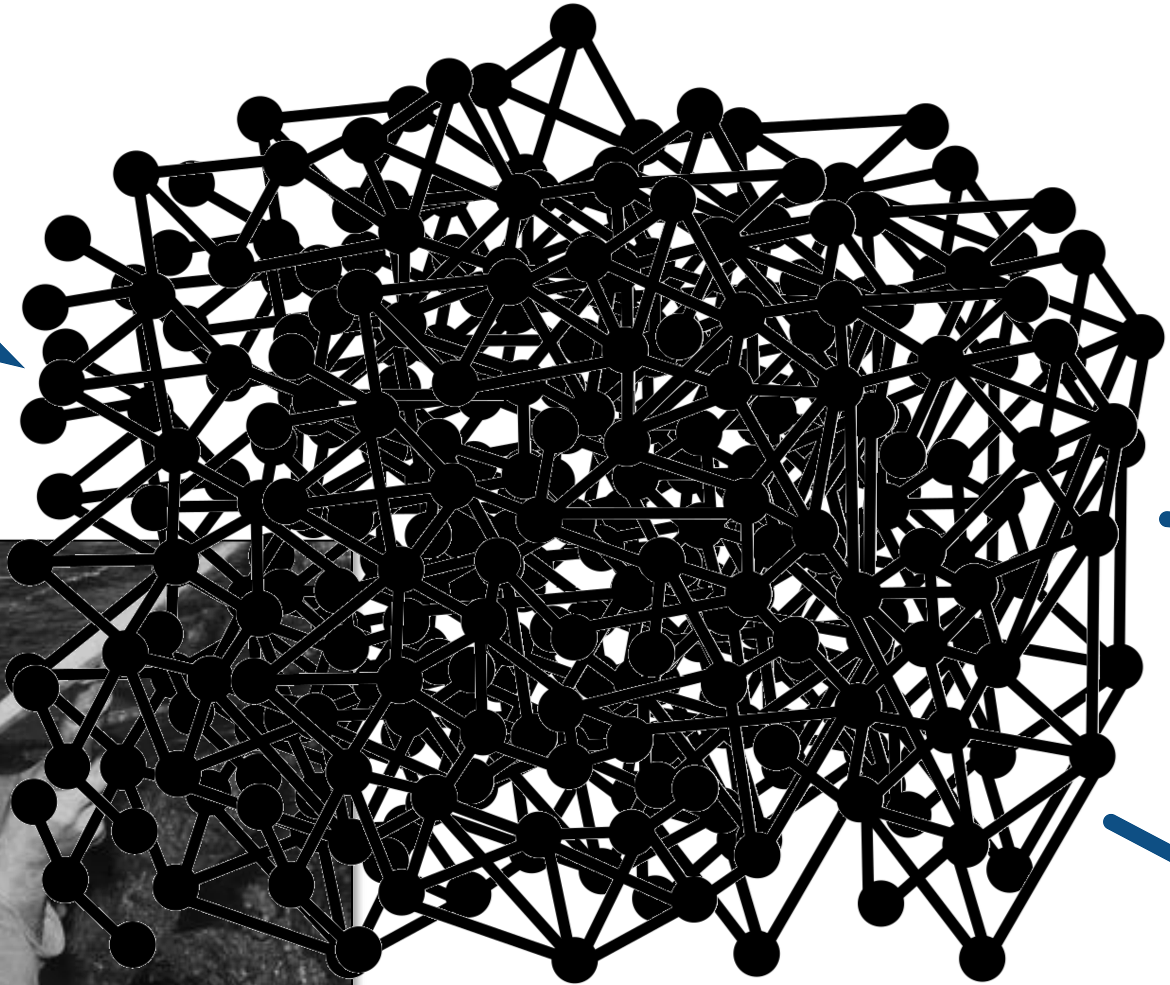

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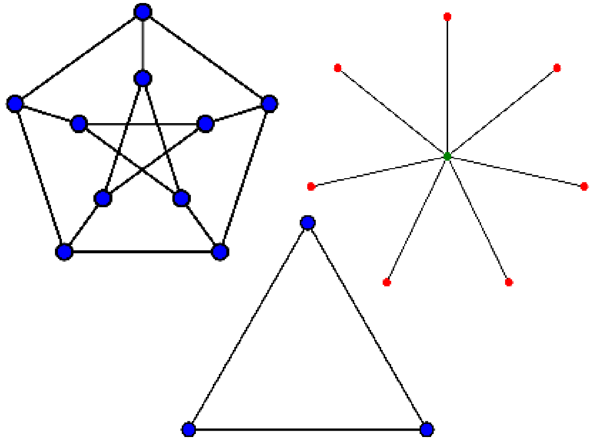
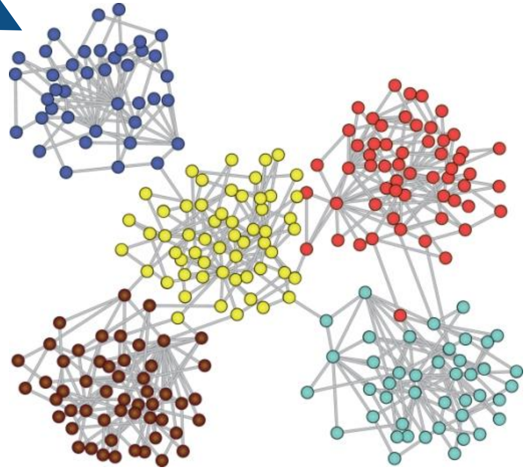
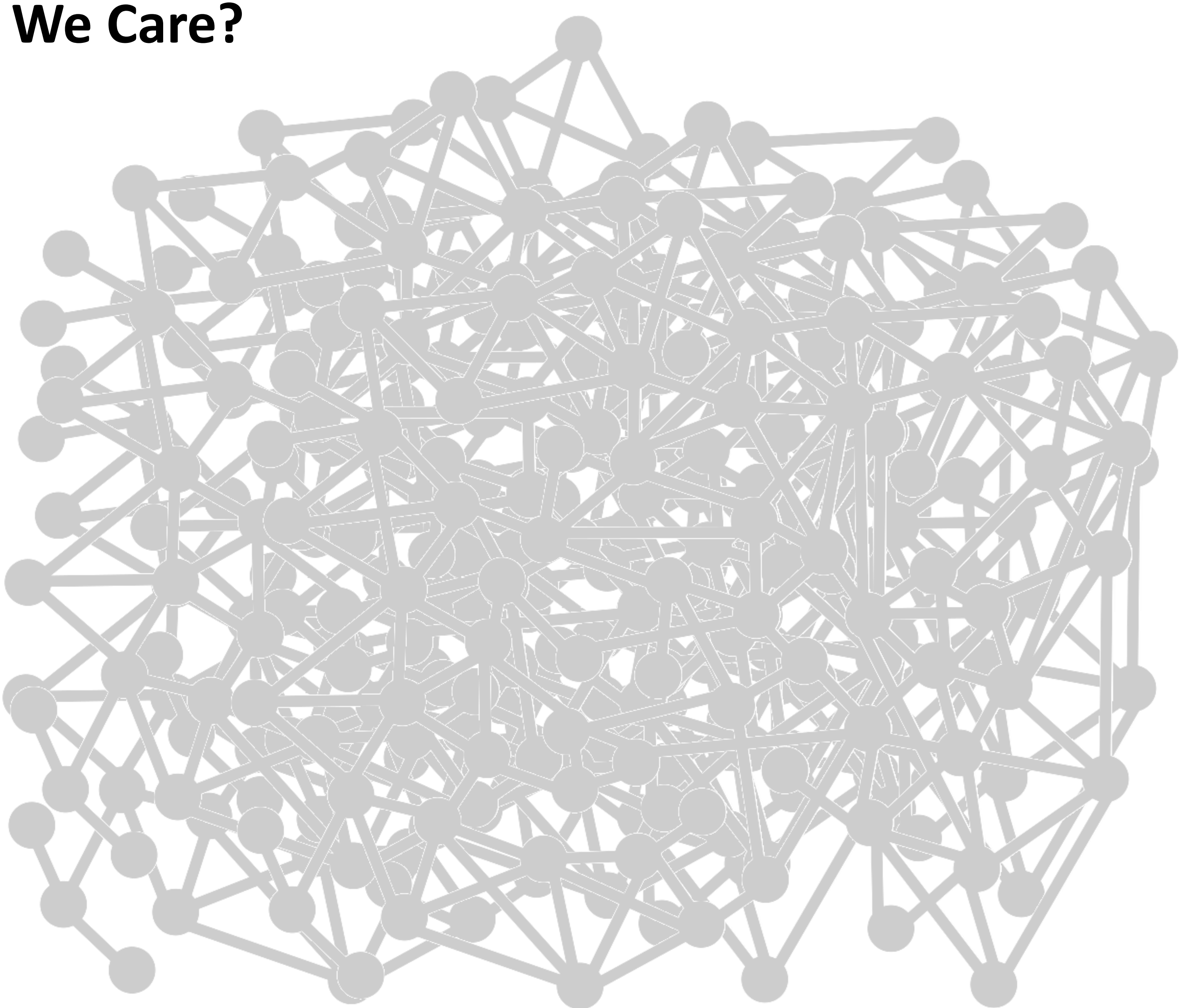


Clustering, Link Prediction, Vertex Similarity, ...

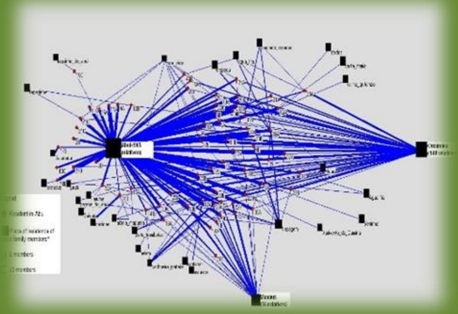


Graph Mining: Do We Care?



Graph Mining: Do We Care?

Social sciences



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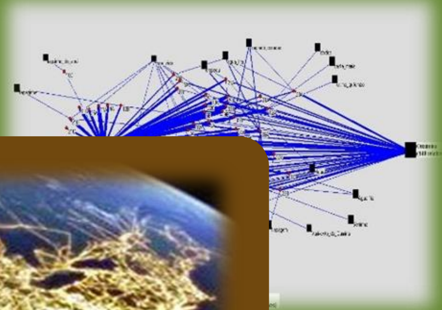
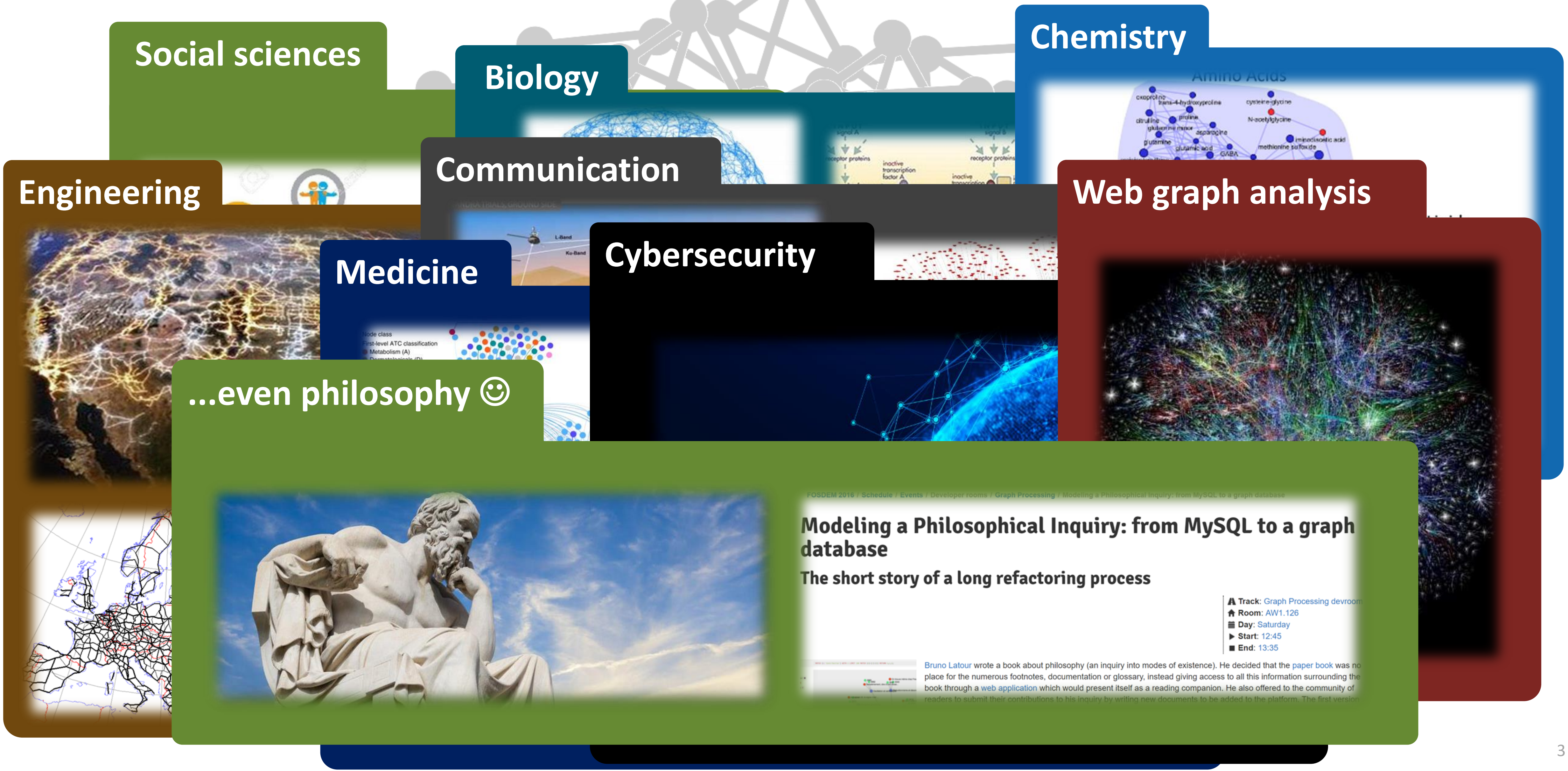


Engineering

Graph Mining: Do We Care?



Graph Mining: Do We Care?

Social sciences

Biology

Chemistry

Communication

Engineering

Web graph analysis

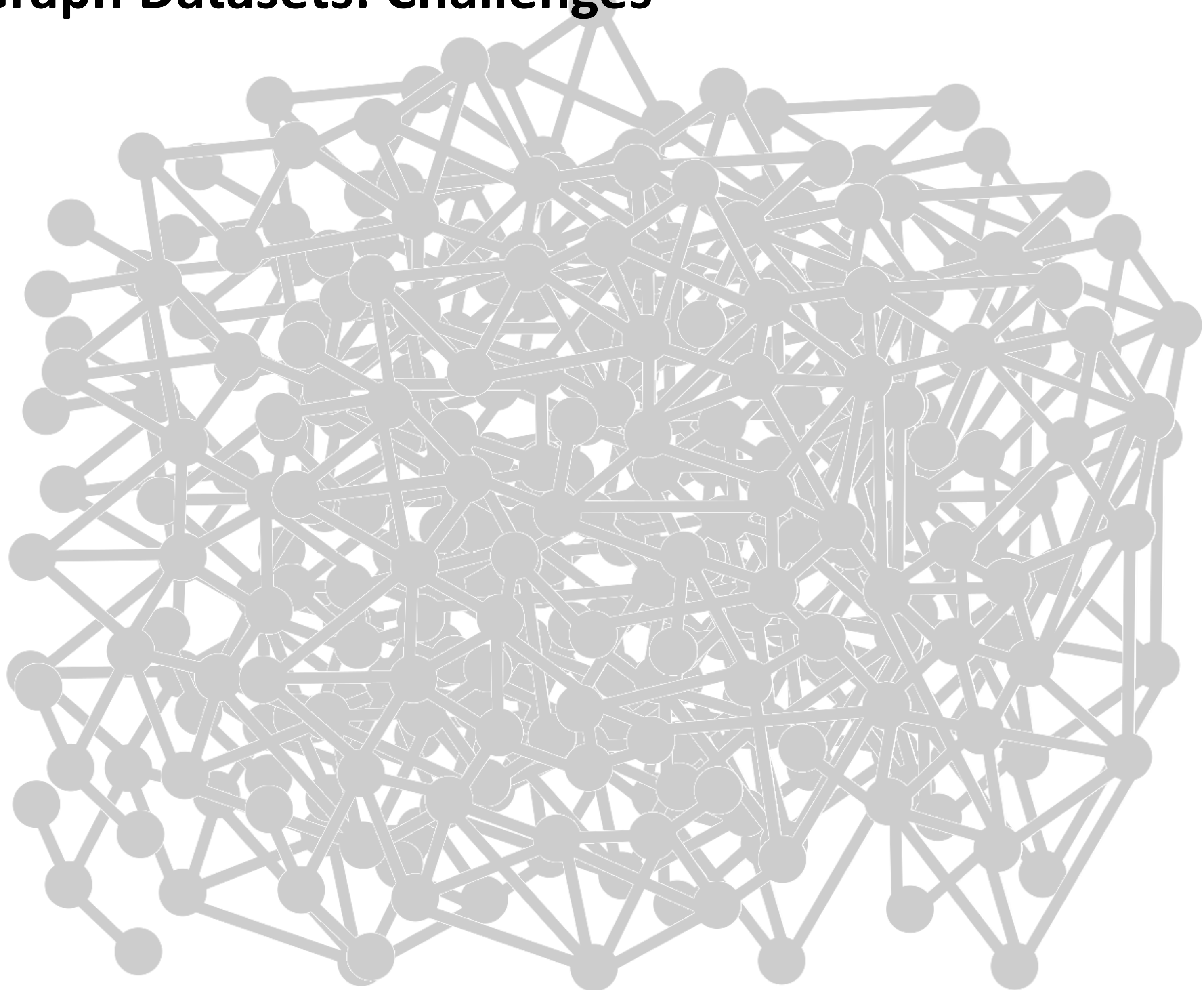
...even philosop

Modeling a Philosophical Inquiry: from MySQL to a graph database

The short story of a long refactoring process

Challenges

Graph Mining & Graph Datasets: Challenges



Graph Mining & Graph Datasets: Challenges

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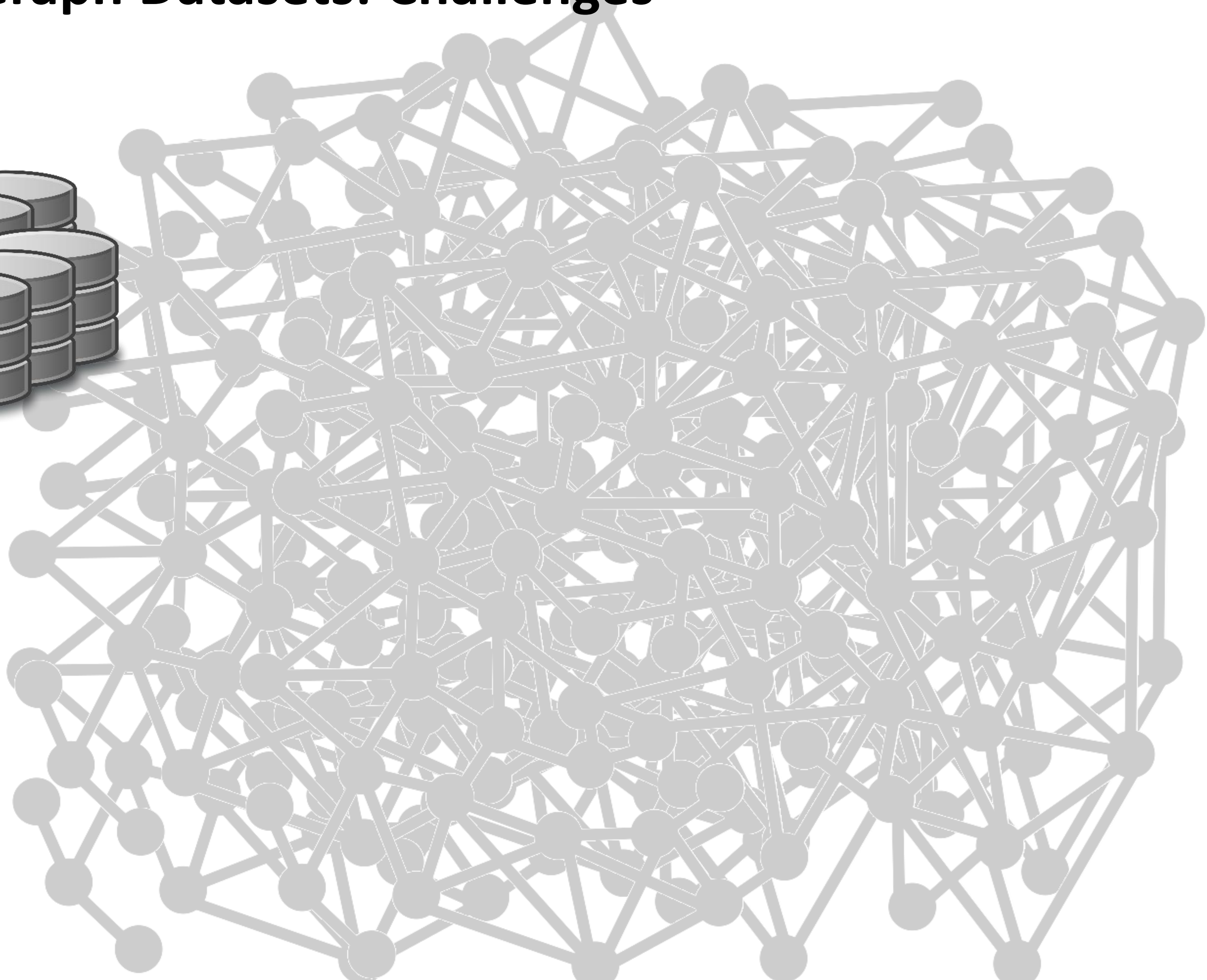

[1] Heng Lin et al.: ShenTu: Processing Multi-Trillion Edge Graphs on Millions of Cores in Seconds, SC18, Gordon Bell Finalist

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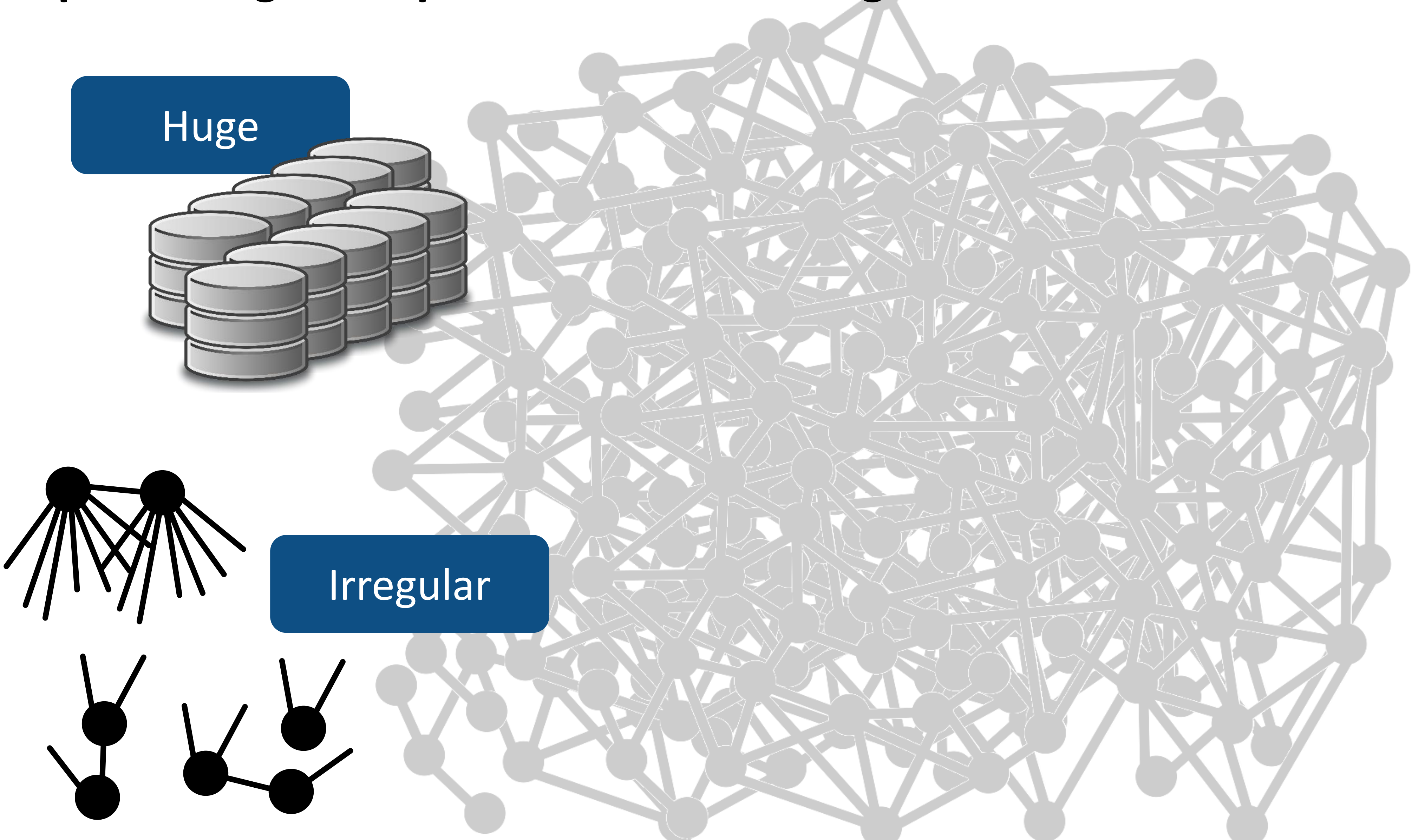

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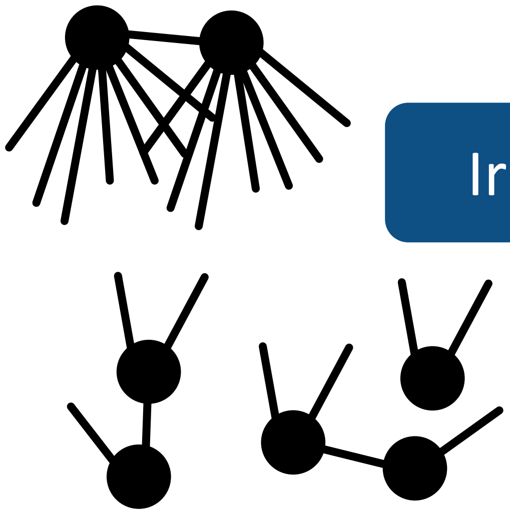
Graph Mining & Graph Datasets: Challenges

Huge

Communication-heavy

Synchronization-heavy



Irregular

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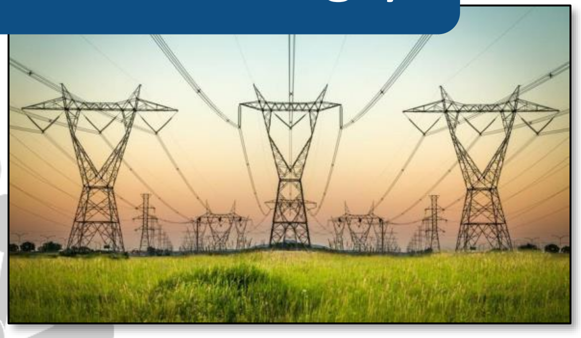

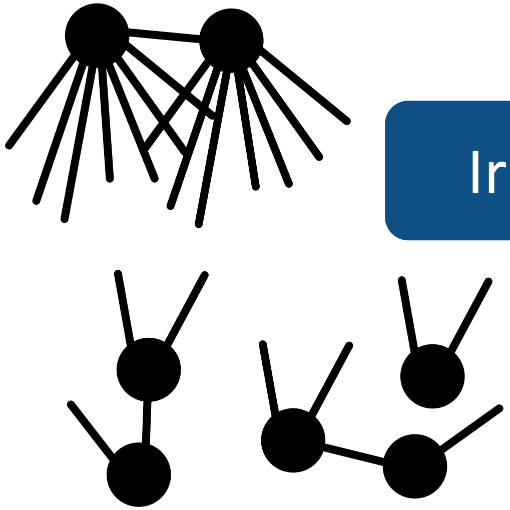

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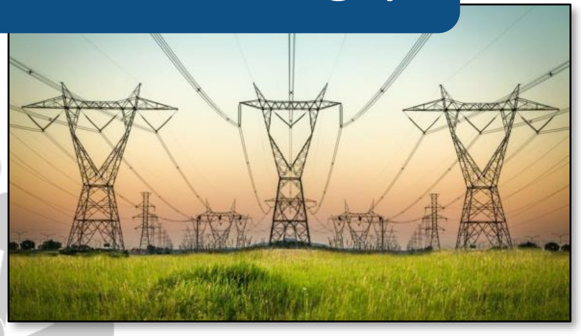
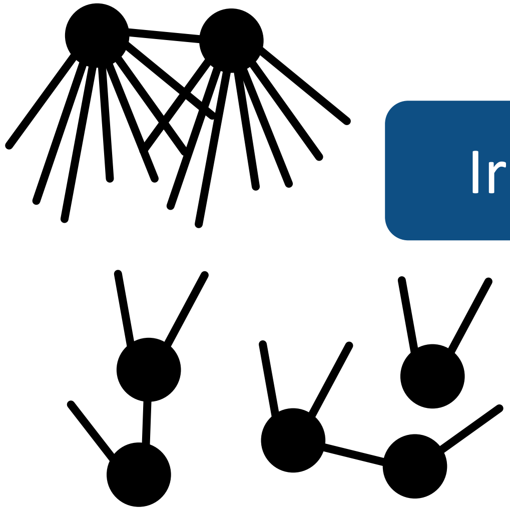
Graph Mining & Graph Datasets: Challenges

Huge

Communication-heavy

Power-hungry





Irregular

Synchronization-heavy

Time complexities often $O(n^k)$ for $k \geq 2$

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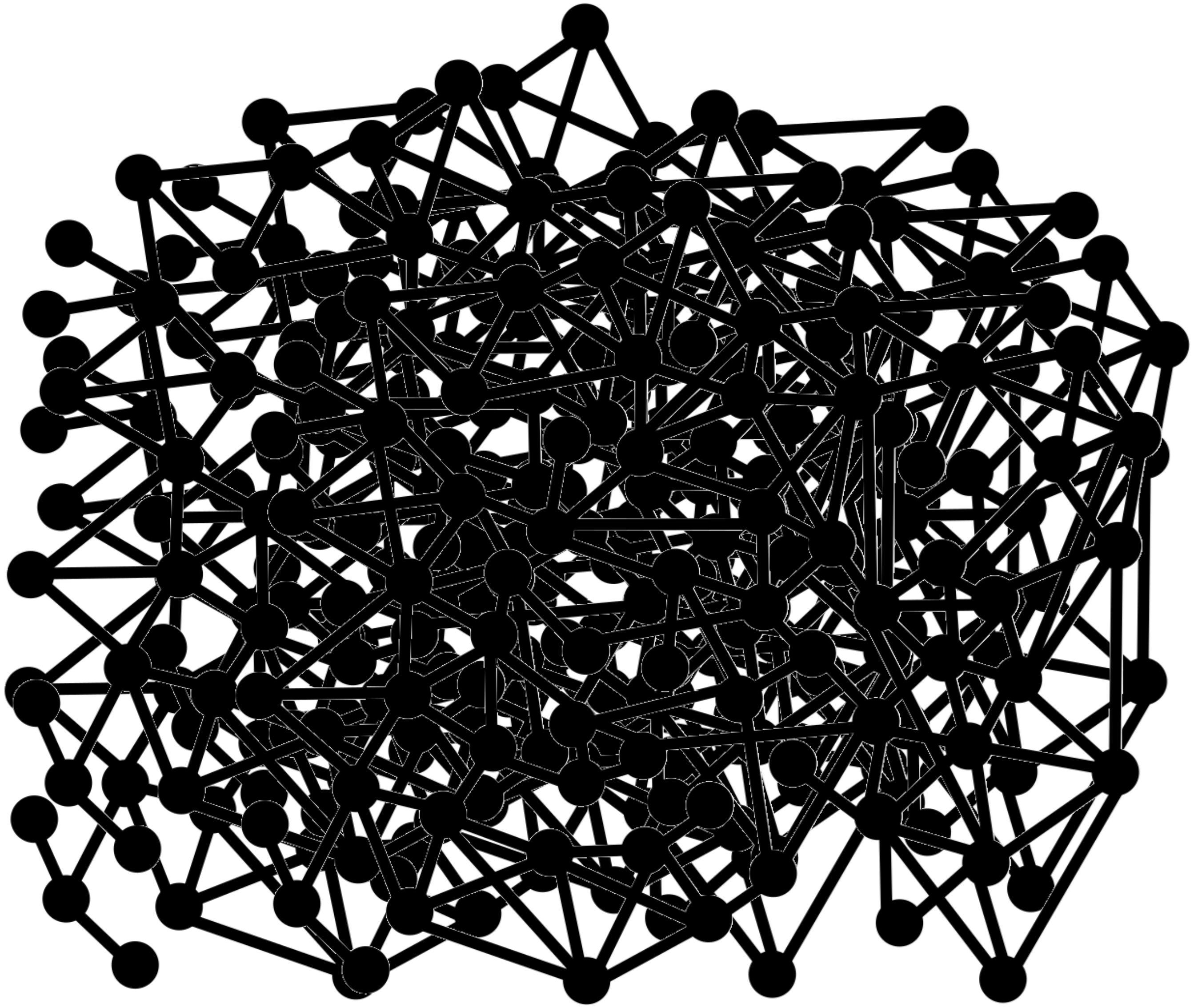
Goal: Making Graph Mining Radically Faster



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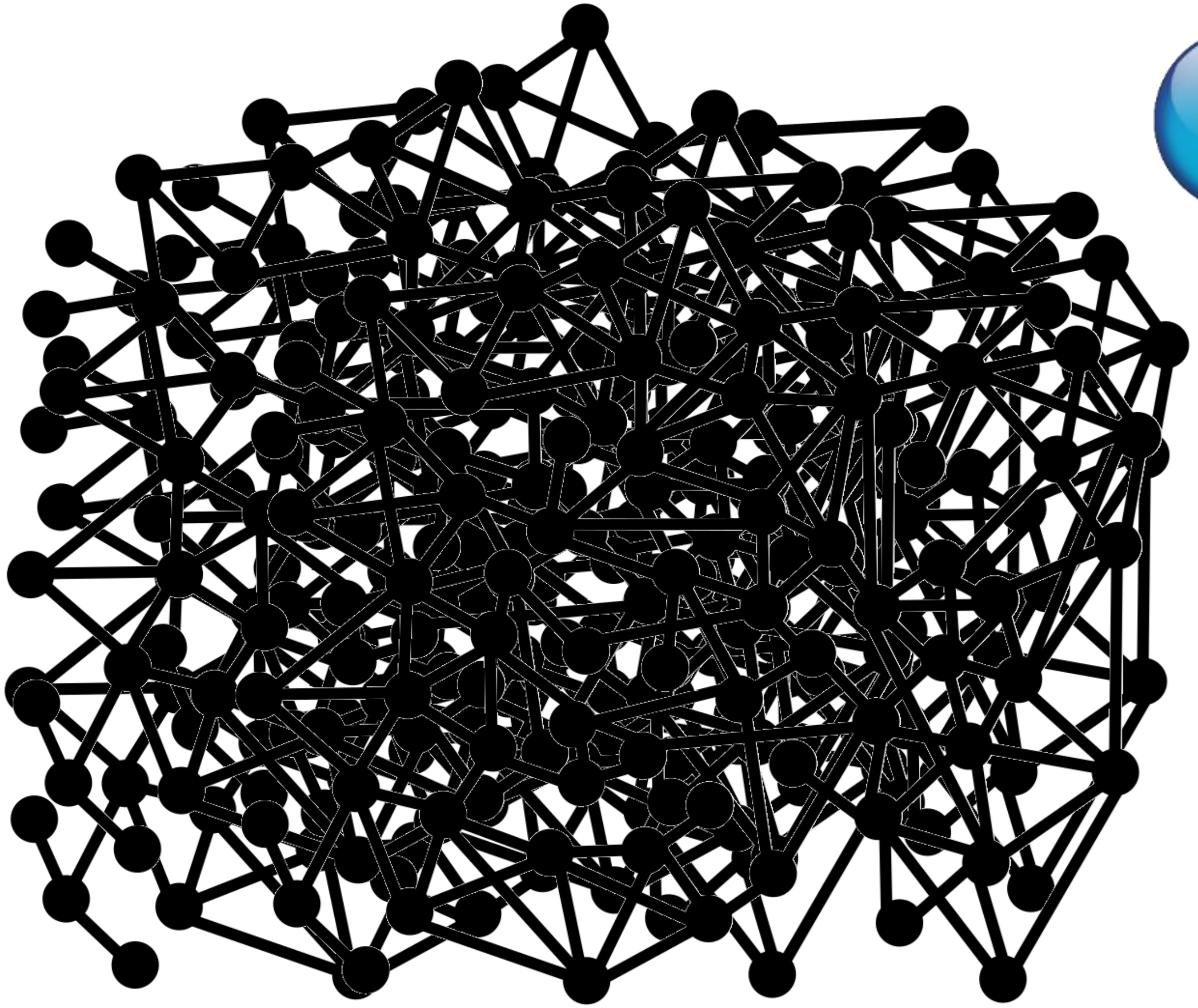

Do we need 100% accurate results in all cases?

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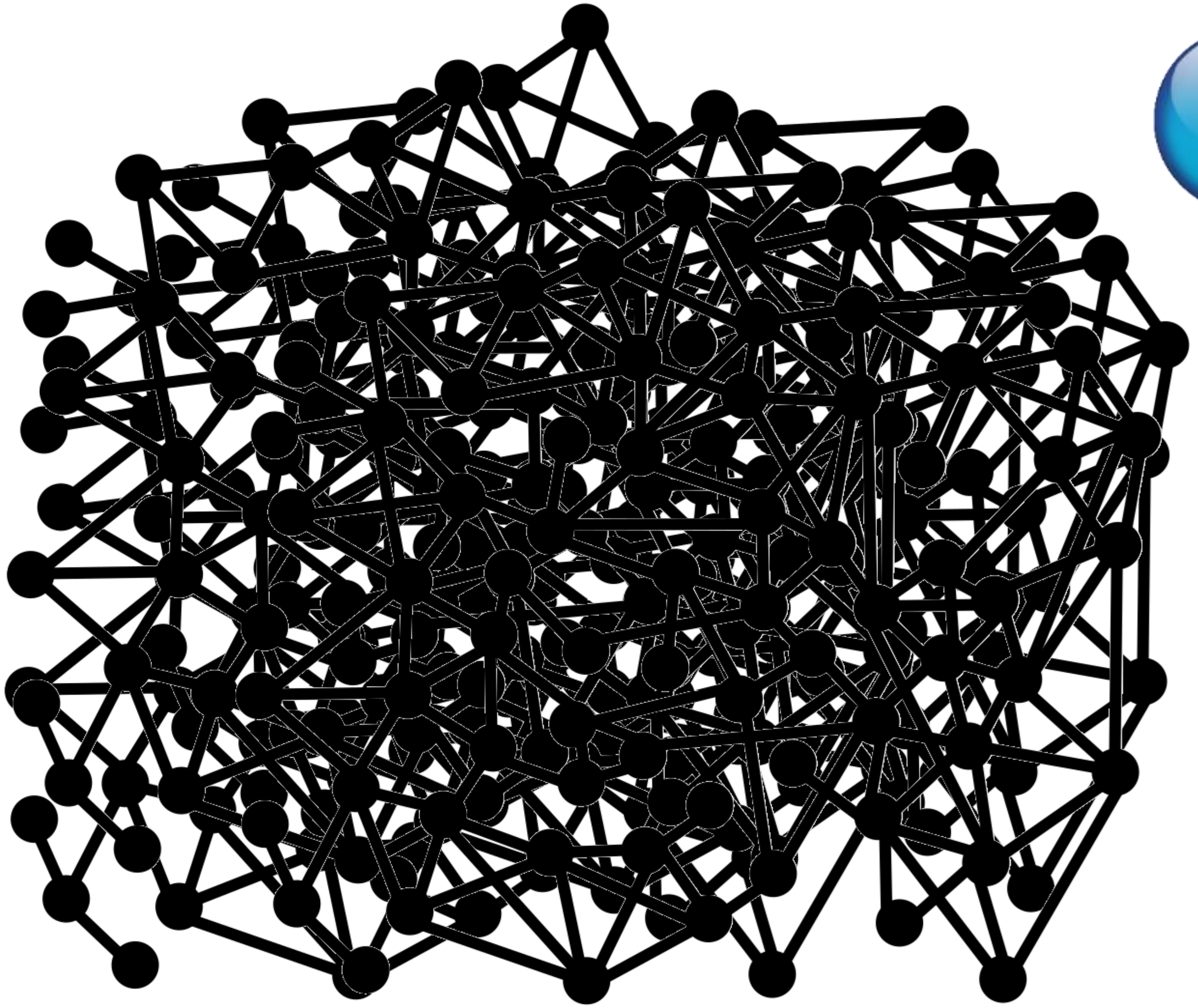

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Let's say we can choose between...

Find all the patterns (e.g., cliques) in 1 day

Find ≥ 90% of all the patterns in 30 minutes

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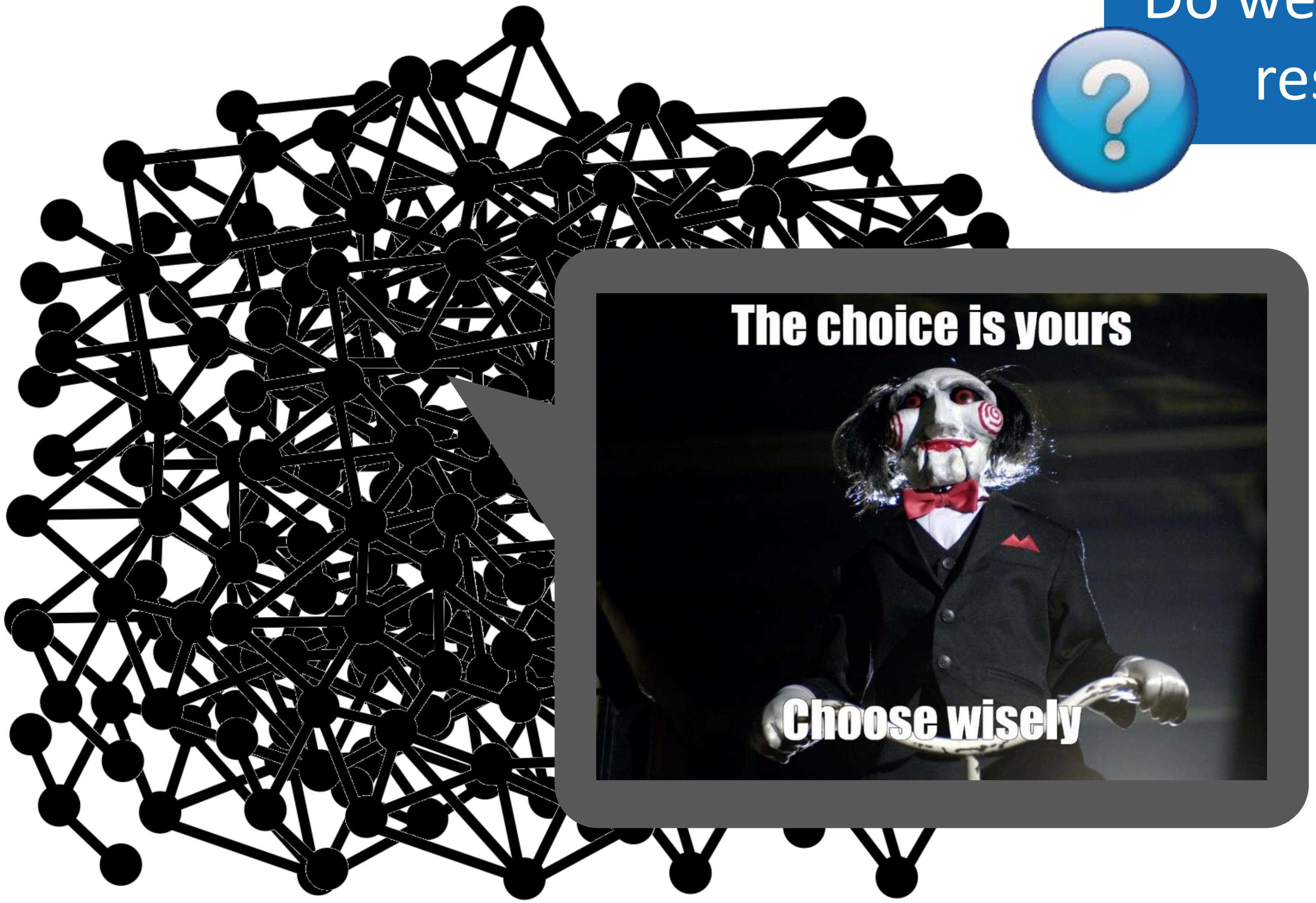

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Approximate Graph Processing: State & Challenges

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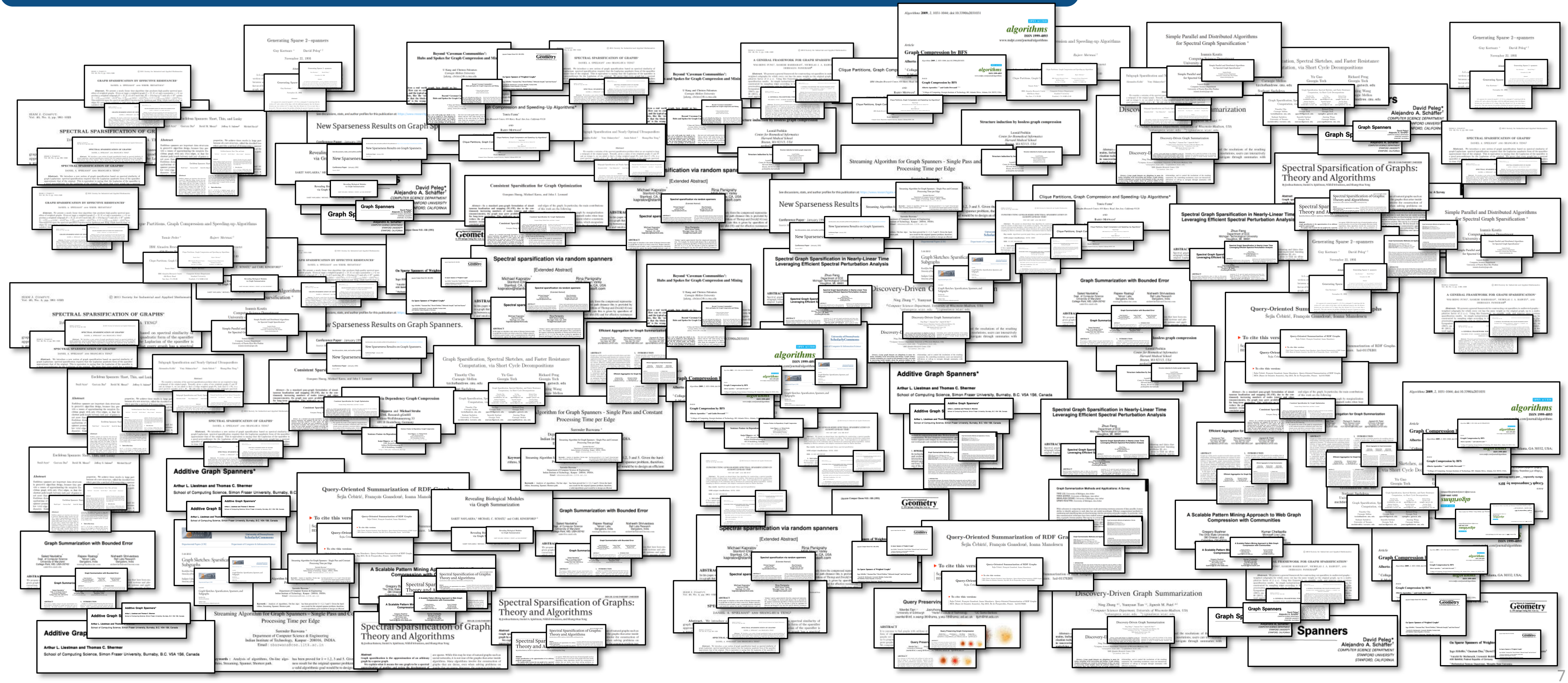
We analyzed > 500 works and identified three classes of schemes...



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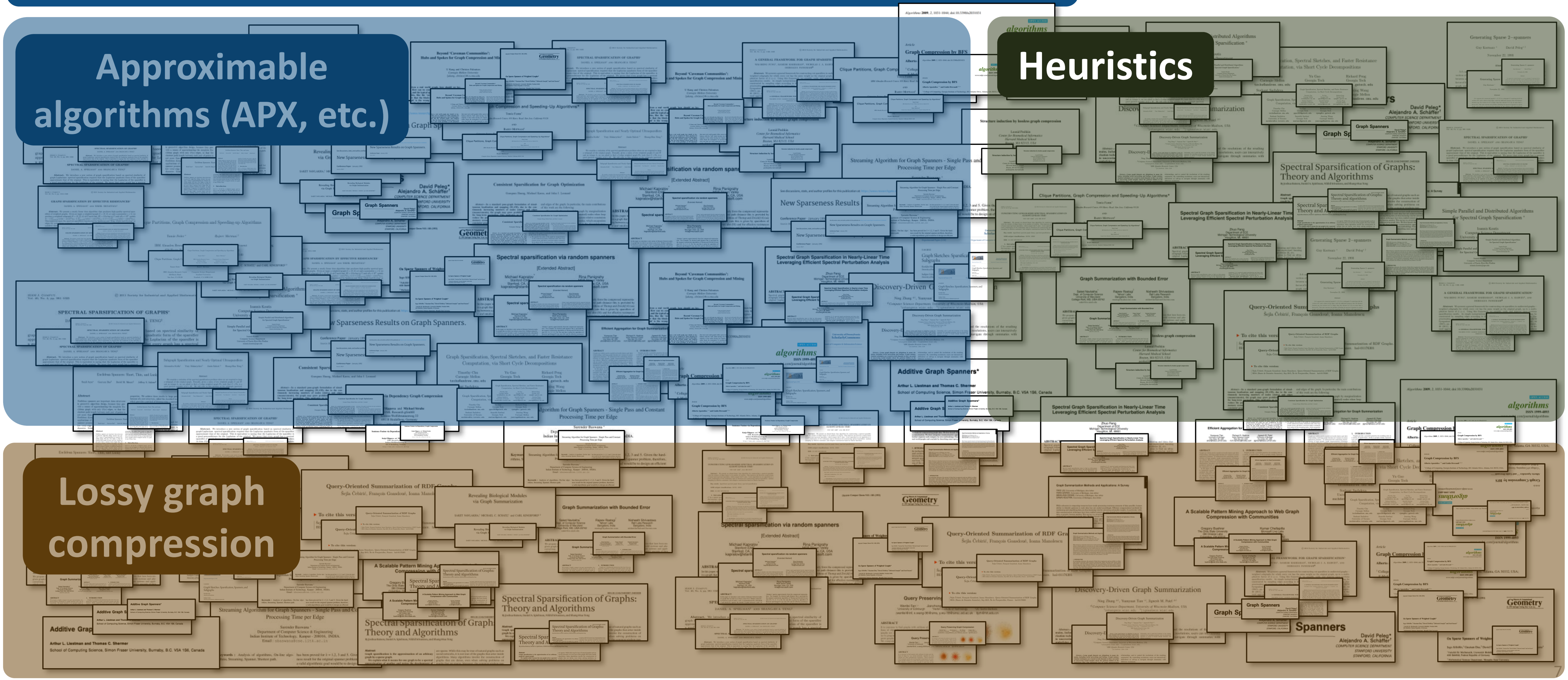

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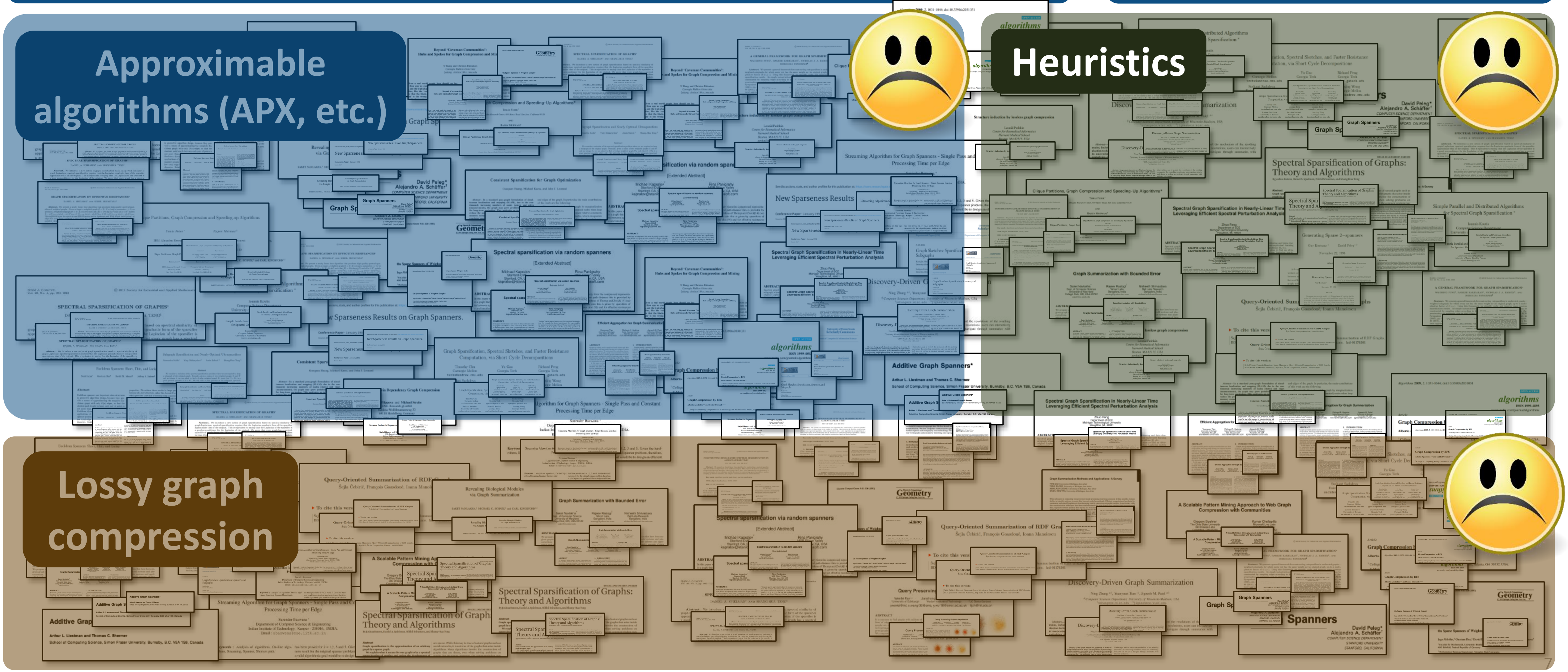

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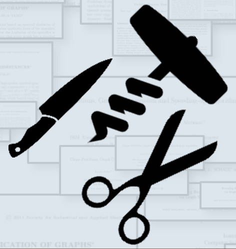
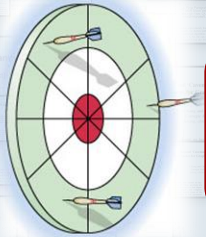
Approximable algorithms (APX, etc.)

Little parallelism



Specific

Slow



Low accuracy

Heuristics

Lossy graph compression

Approximate Graph Processing: State & Challenges

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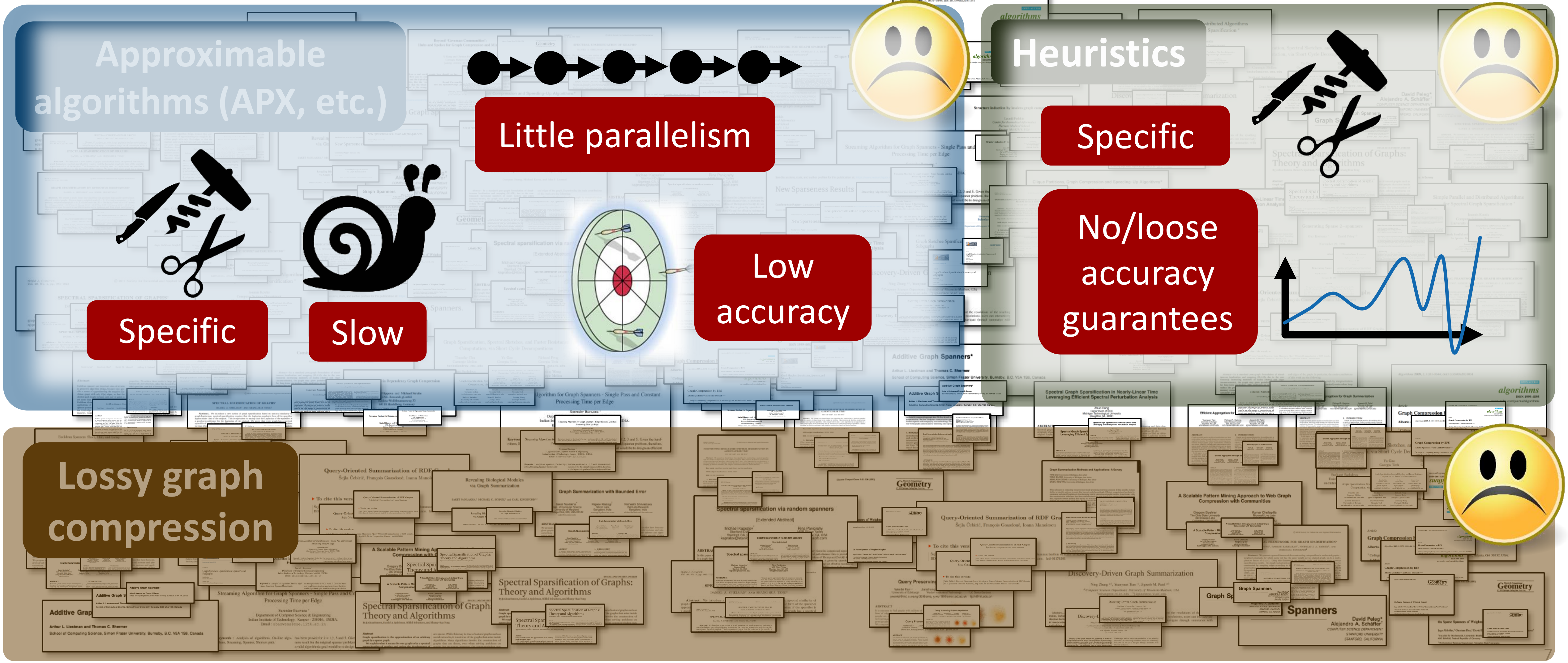

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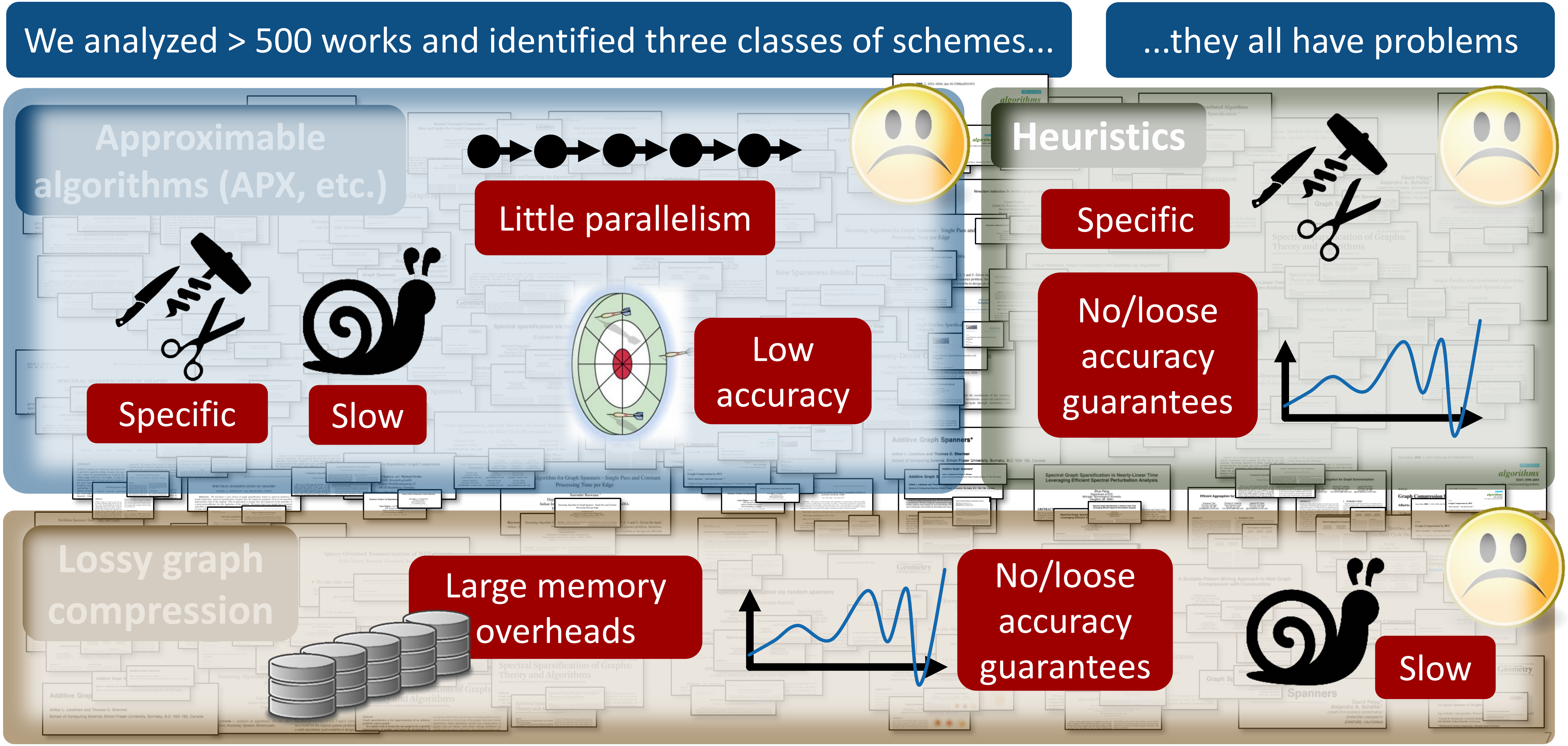

Approximate Graph Processing: Current Issues & Our Objectives

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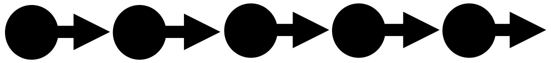

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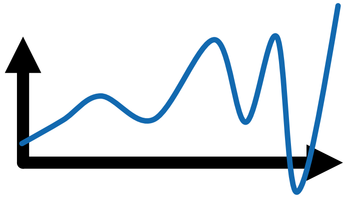
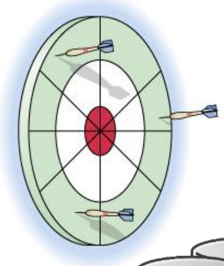


No/loose accuracy guarantees

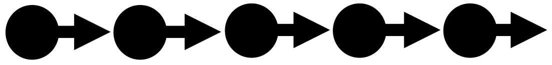
Slow



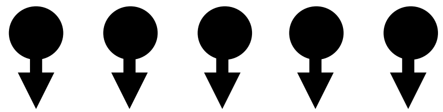
Low accuracy

Large memory overheads

Approximate Graph Processing: Current Issues & Our Objectives



Little parallelism → Rich parallelism



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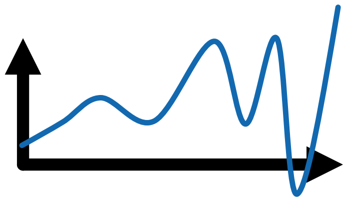

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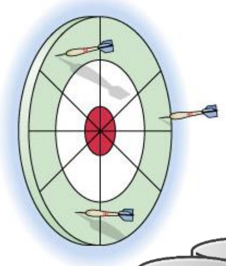

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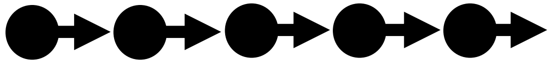

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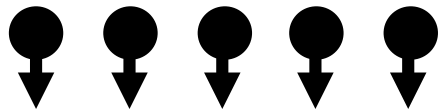
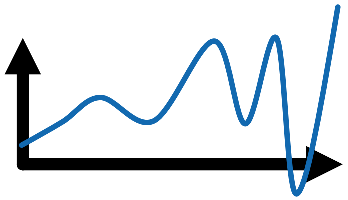


Specific → Wide applicability



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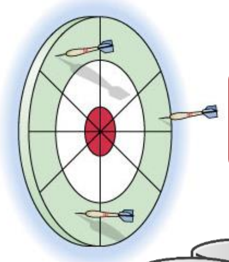
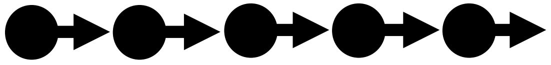


Low accuracy

Large memory overheads

Approximate Graph Processing: Current Issues & Our Objectives



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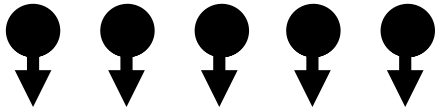

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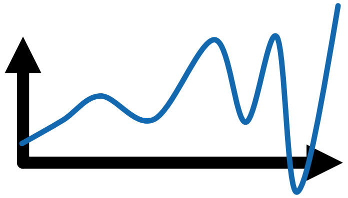
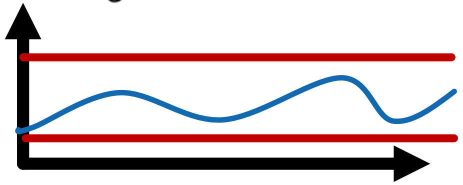


No/loose accuracy guarantees → Strong accuracy guarantees



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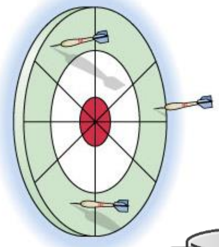
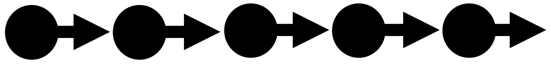


Low accuracy

Large memory overheads

Approximate Graph Processing: Current Issues & Our Objectives



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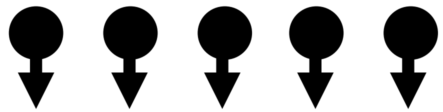

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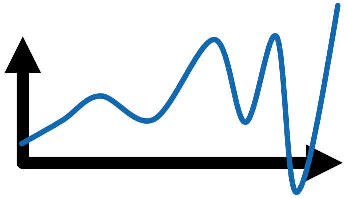

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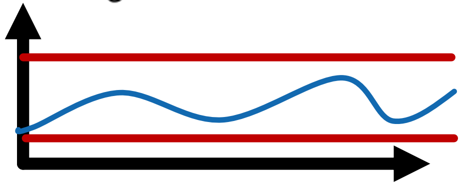
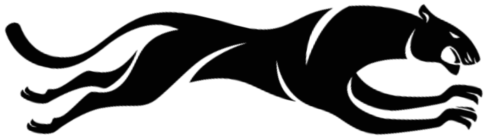
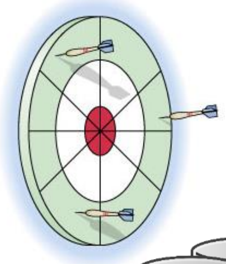


Slow → High performance





Low accuracy

Large memory overheads

Approximate Graph Processing: Current Issues & Our Objectives

Current Issues		Our Objectives
Little parallelism	→	Rich parallelism
Specific	→	Wide applicability
No/loose accuracy guarantees	→	Strong accuracy guarantees
Slow	→	High performance
Low accuracy	→	High accuracy
Large memory overheads		

Approximate Graph Processing: Current Issues & Our Objectives

Current issues		Our objectives
Little parallelism	→	Rich parallelism
Specific	→	Wide applicability
No/loose accuracy guarantees	→	Strong accuracy guarantees
Slow	→	High performance
Low accuracy	→	High accuracy
Large memory overheads	→	Low & controllable memory overheads

Approximate Graph Processing: Current Issues & Our Objectives

How to achieve all these objectives in a single design?

No/loose accuracy guarantees	Strong accuracy guarantees
Slow	High performance
Low accuracy	High accuracy
Large memory overheads	Low & controllable memory overheads

Approximate Graph Processing: Current Issues & Our Objectives

No/loose accuracy guarantees

Strong accuracy guarantees

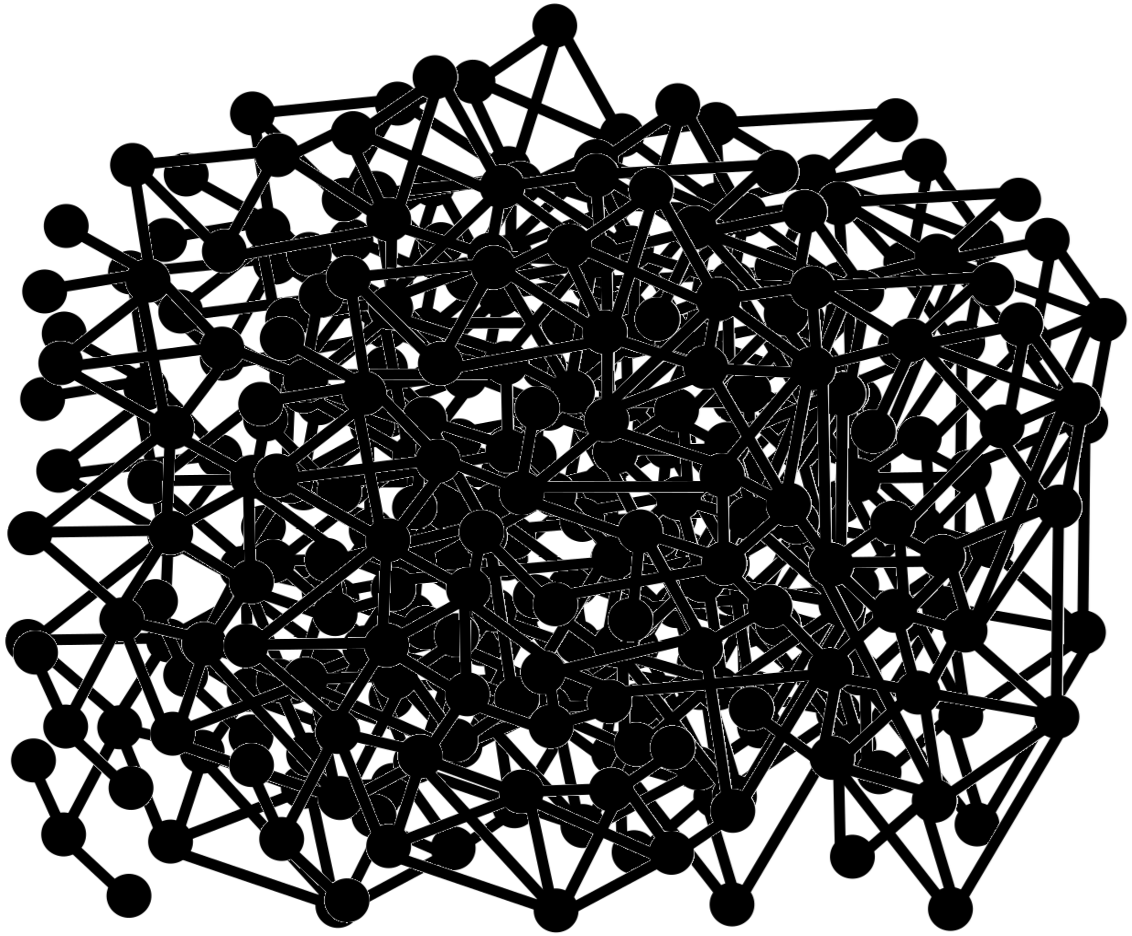
overheads

memory overheads

How to achieve all these objectives in a single design?

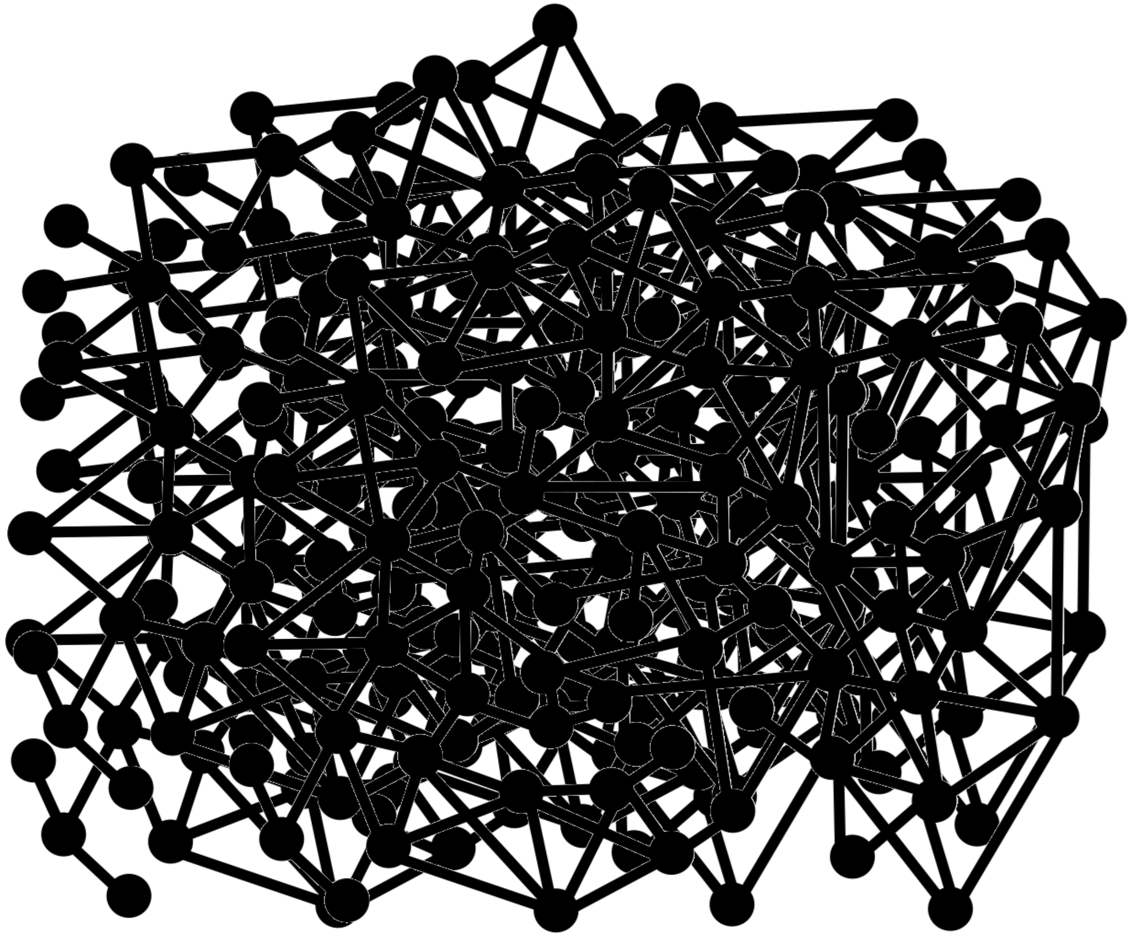
We develop **ProbGraph**: a graph representation that uses probabilistic set representations (aka sketches)

High-Level Approach Taken in ProbGraph



High-Level Approach Taken in ProbGraph

Keep the original graph



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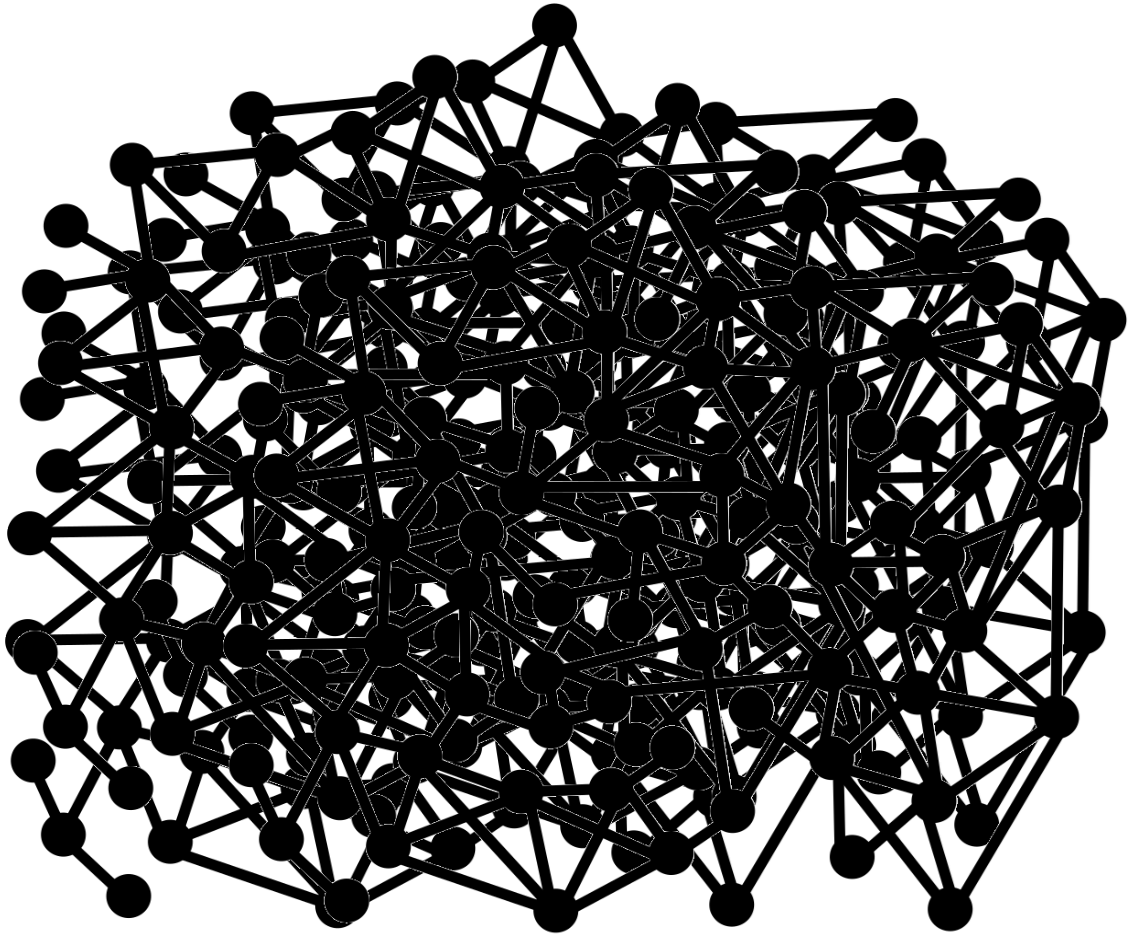

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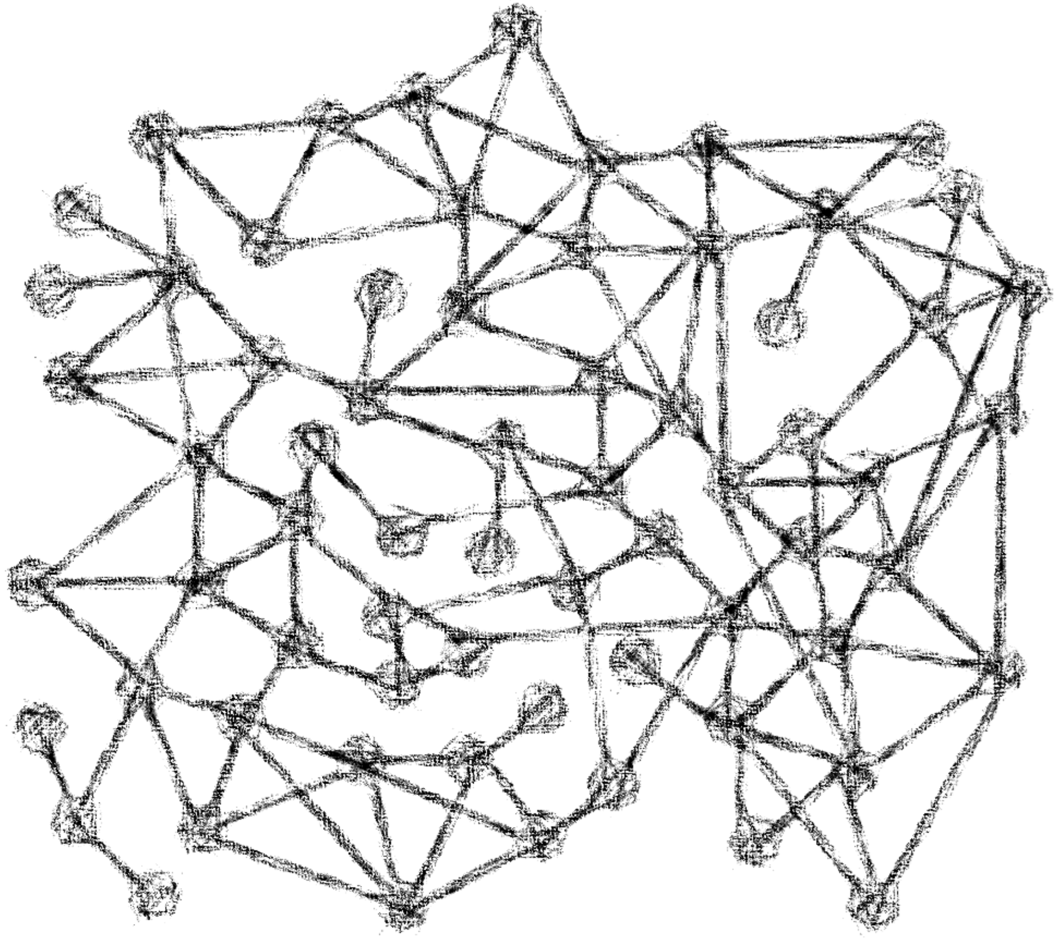
Maintain a very small "sketch" of a graph



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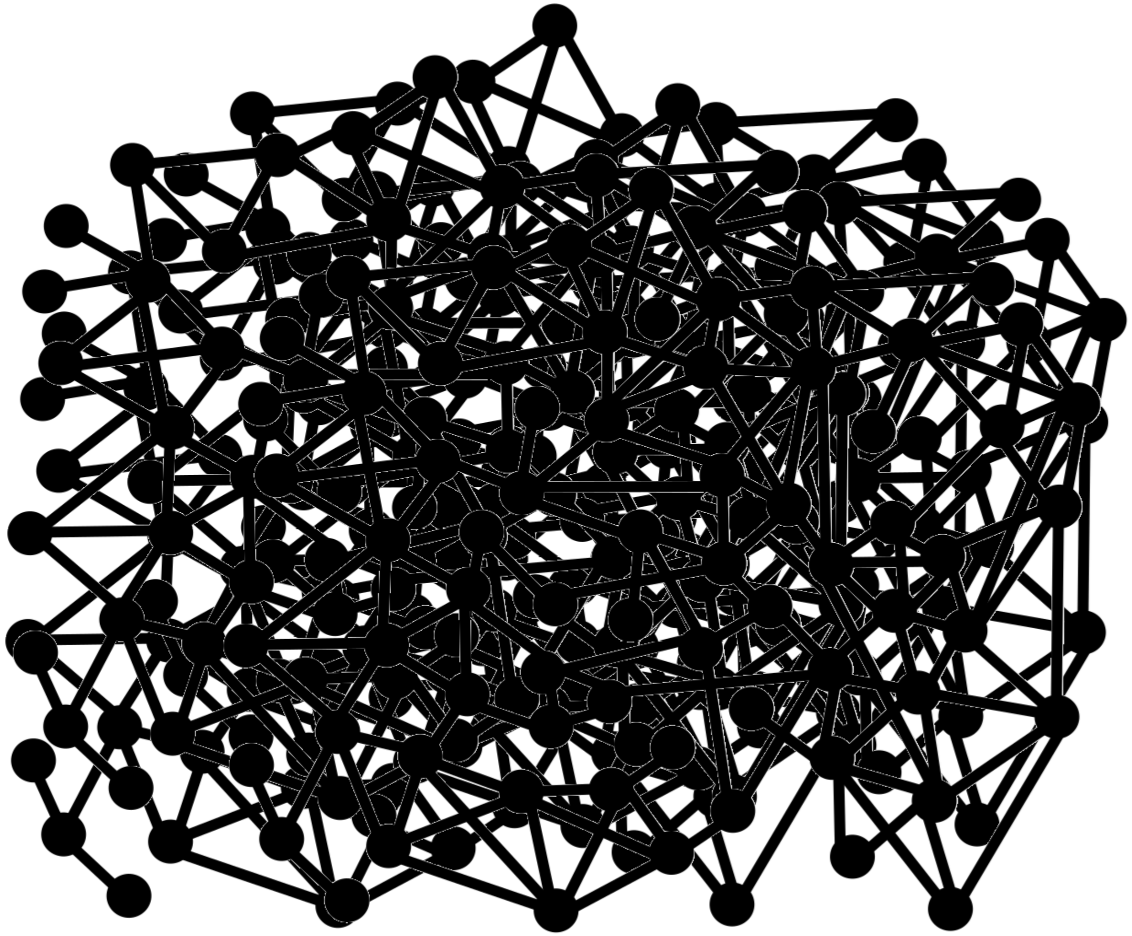

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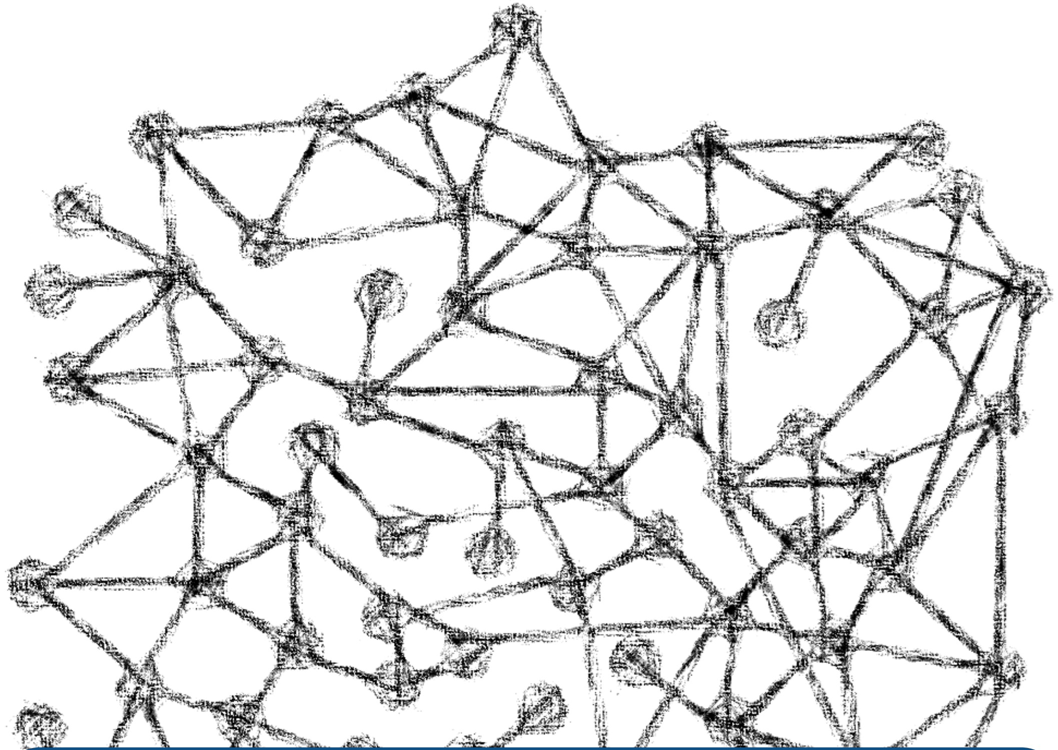

Use the sketch to answer performance critical queries

High-Level Approach Taken in ProbGraph

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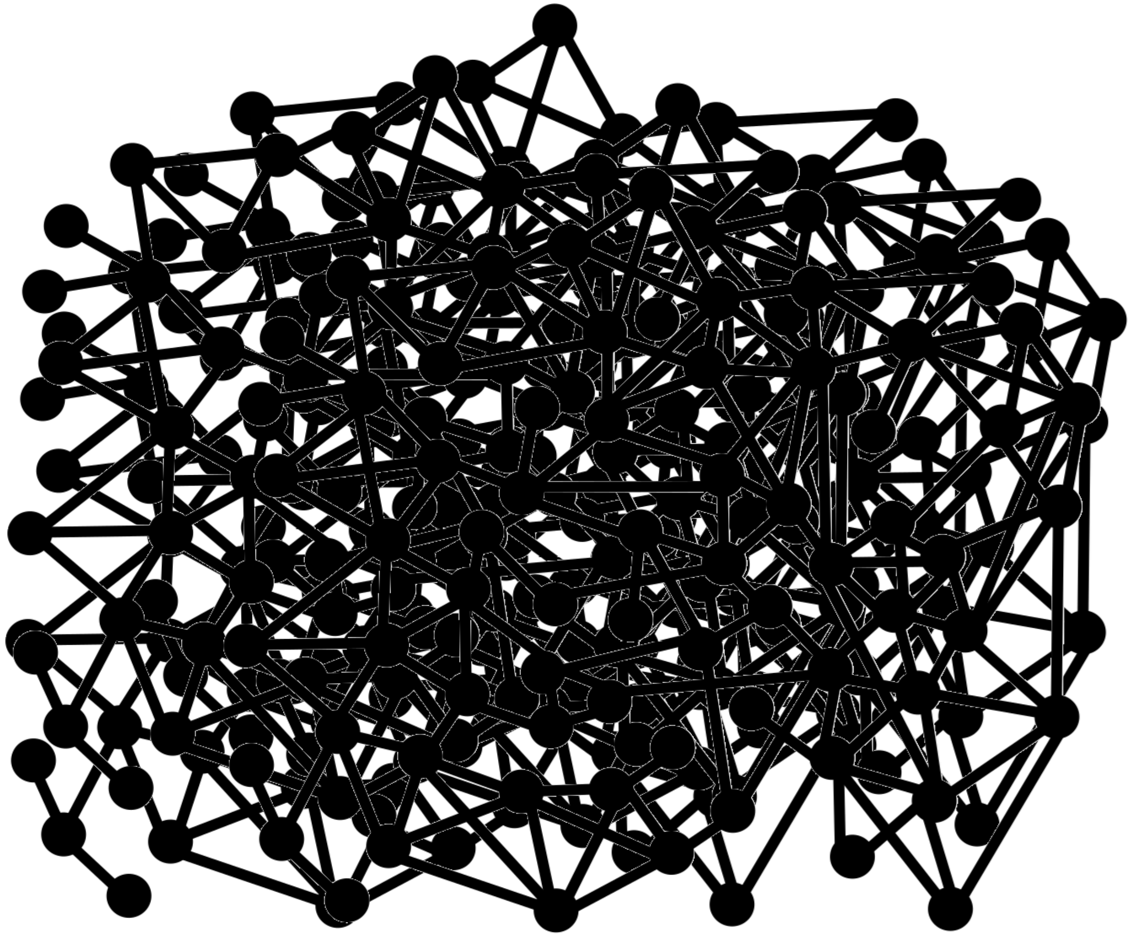

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Maintain a very small "sketch" of a graph

What design to use for the sketch, to satisfy all the goals?

Use the sketch to answer performance critical queries

<u>ProbGraph key idea</u>: Use probabilistic set representations (set sketches)

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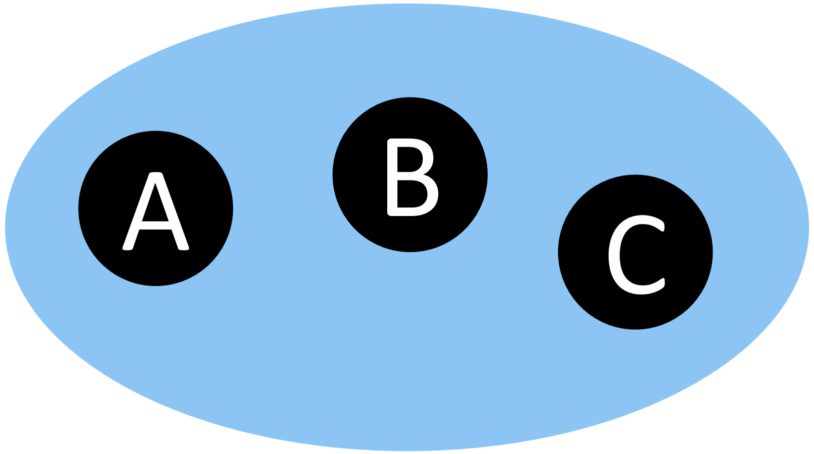
A set = {A, B, C}



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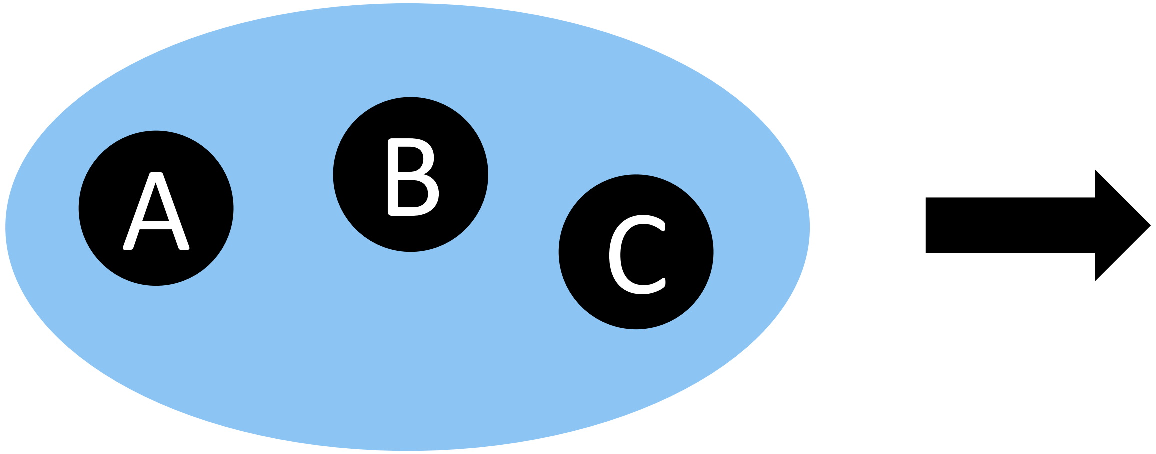

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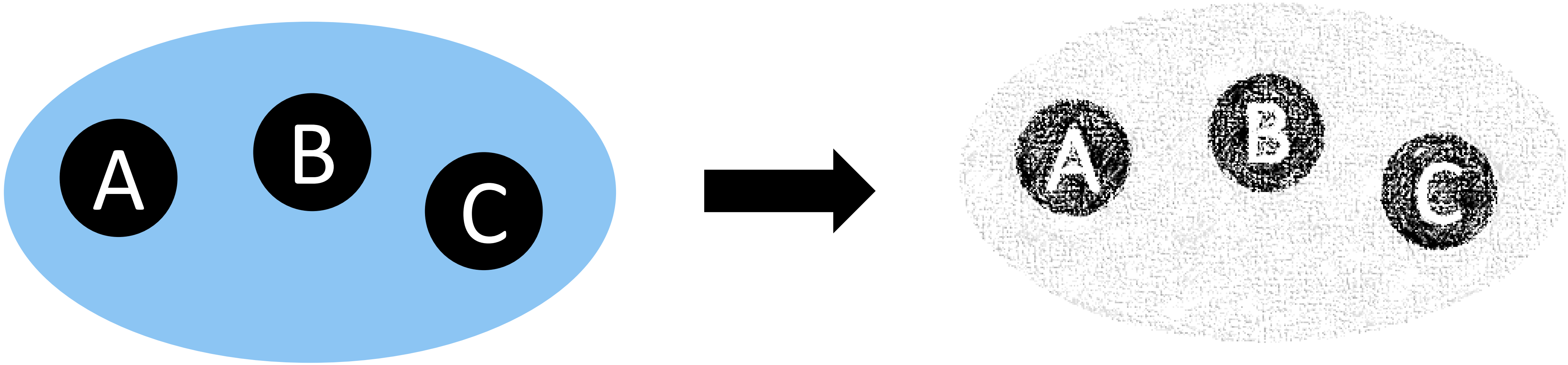

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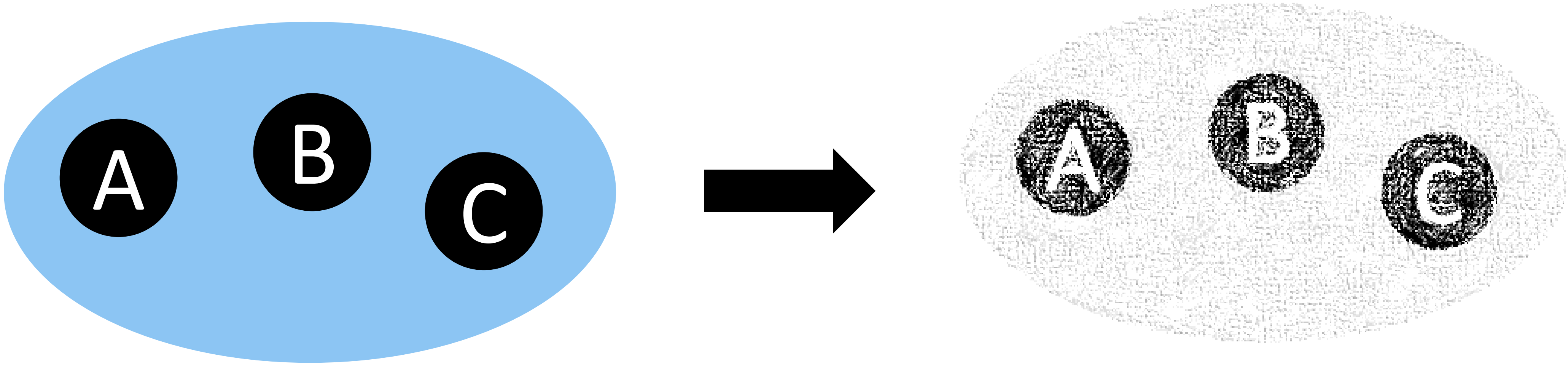

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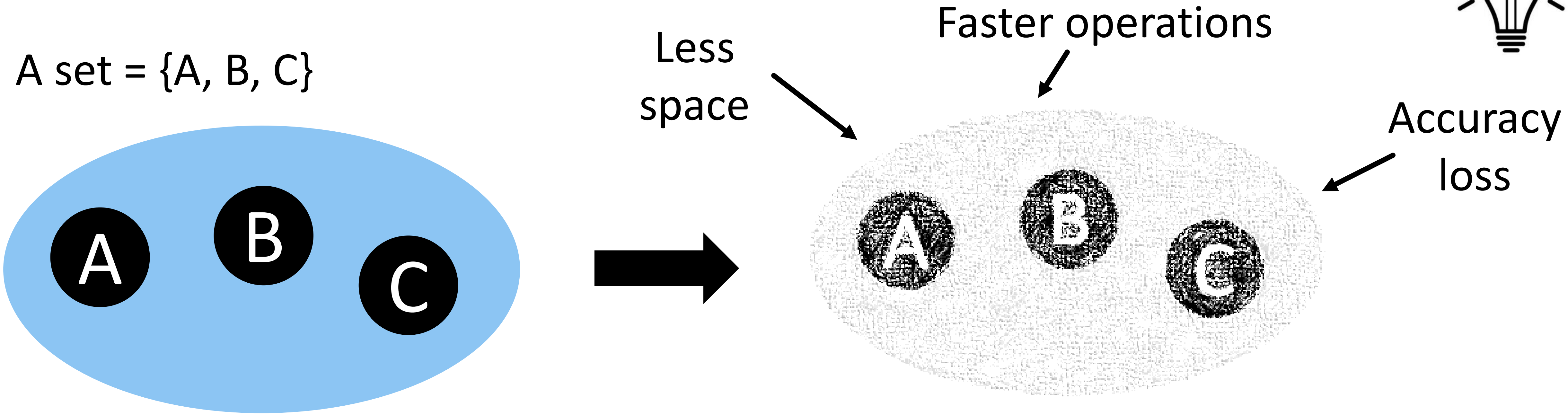

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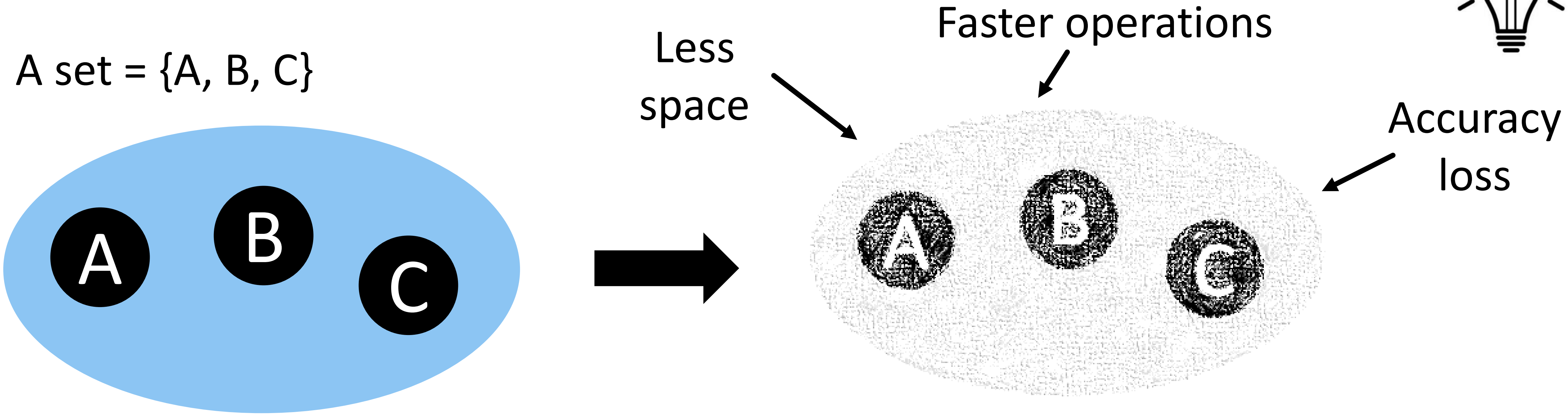

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Bloom Filters for Graph Mining

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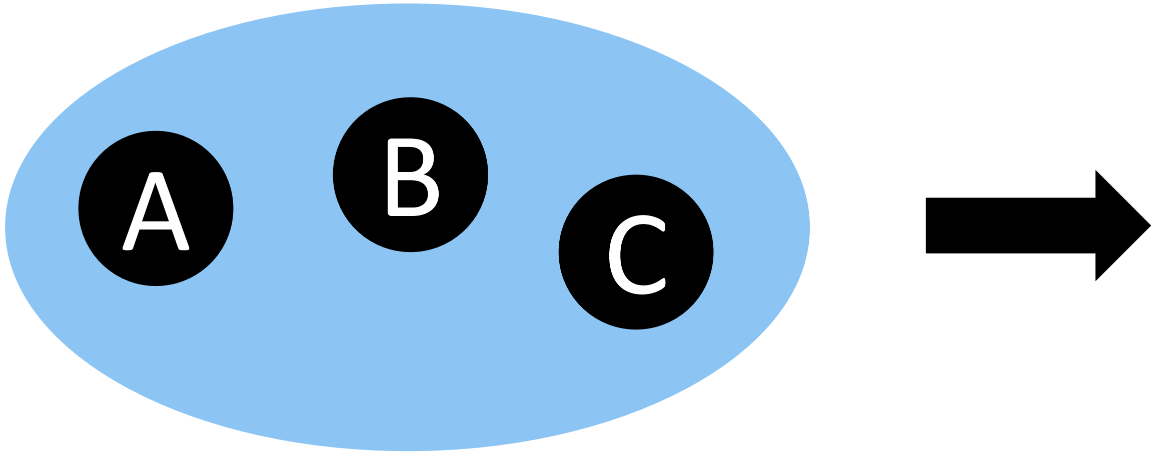

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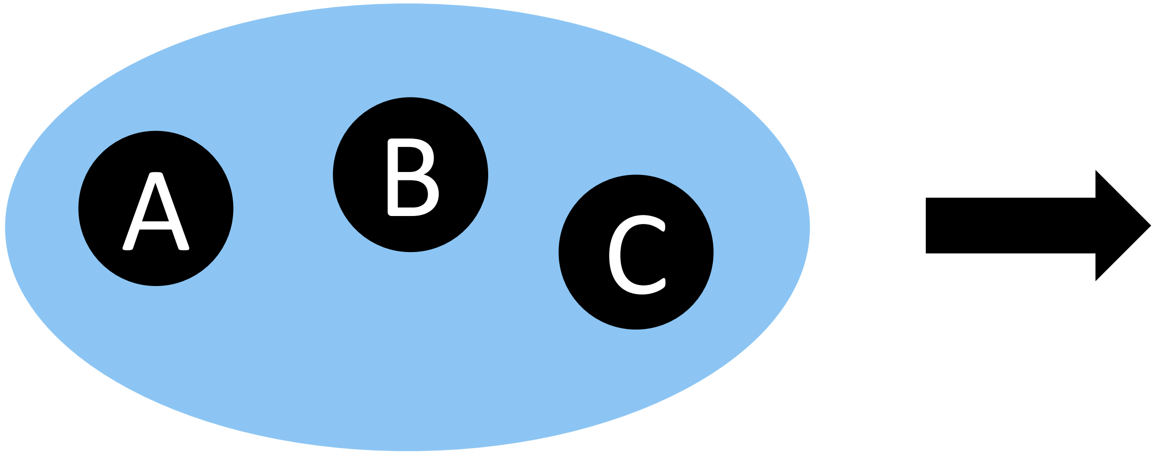

Bloom filter $\mathcal{B}_X$ of X

Bitvector of size B_X [bits]

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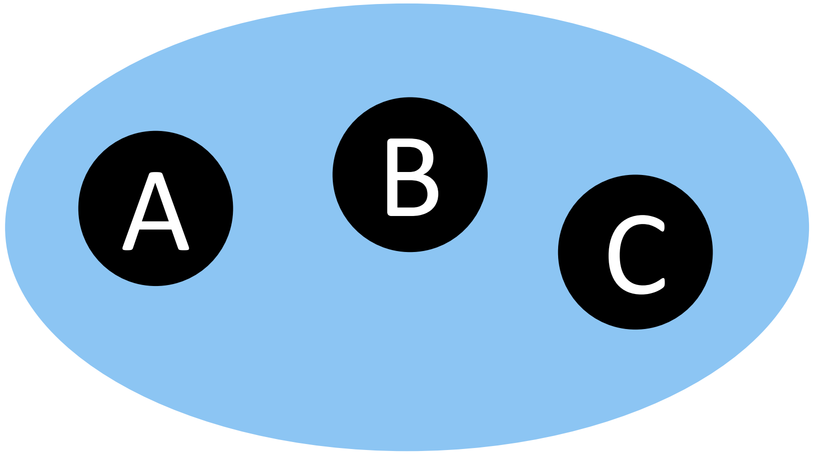

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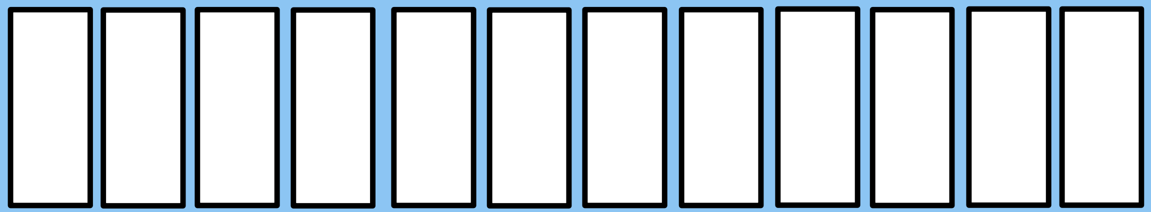
Bitvector of size B_X [bits]

$B_X = 12$



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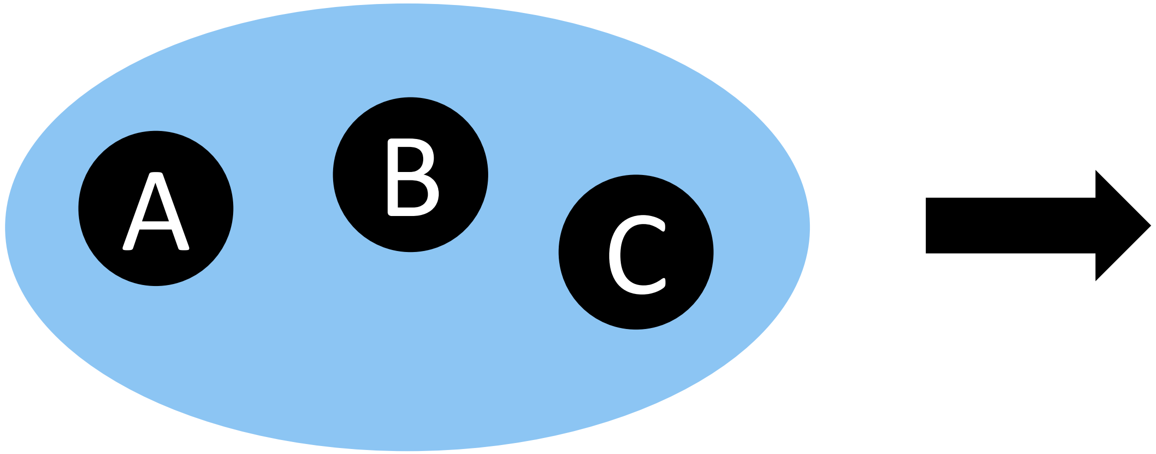

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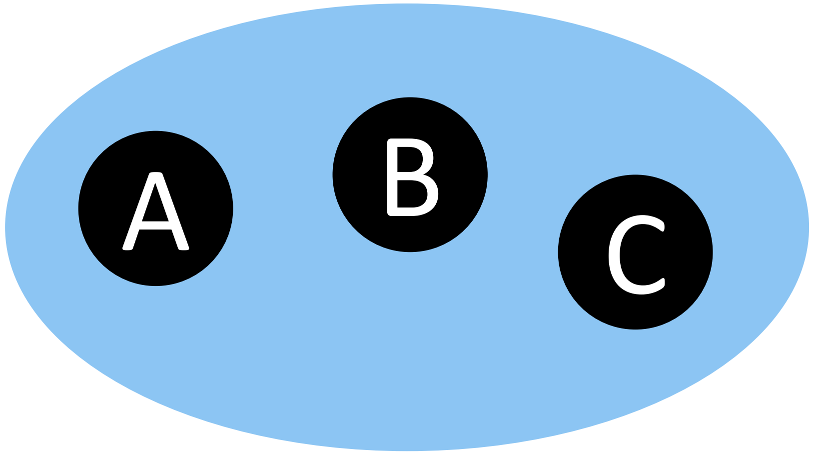

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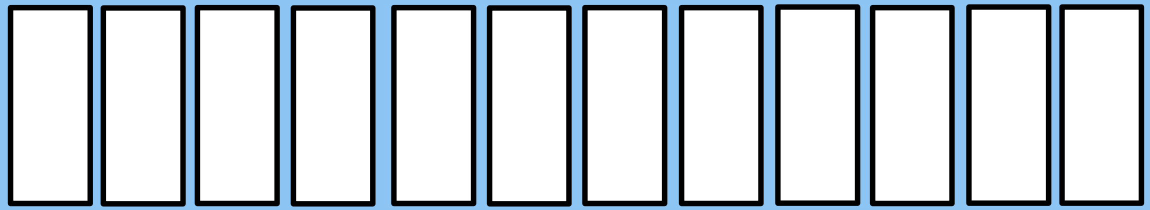

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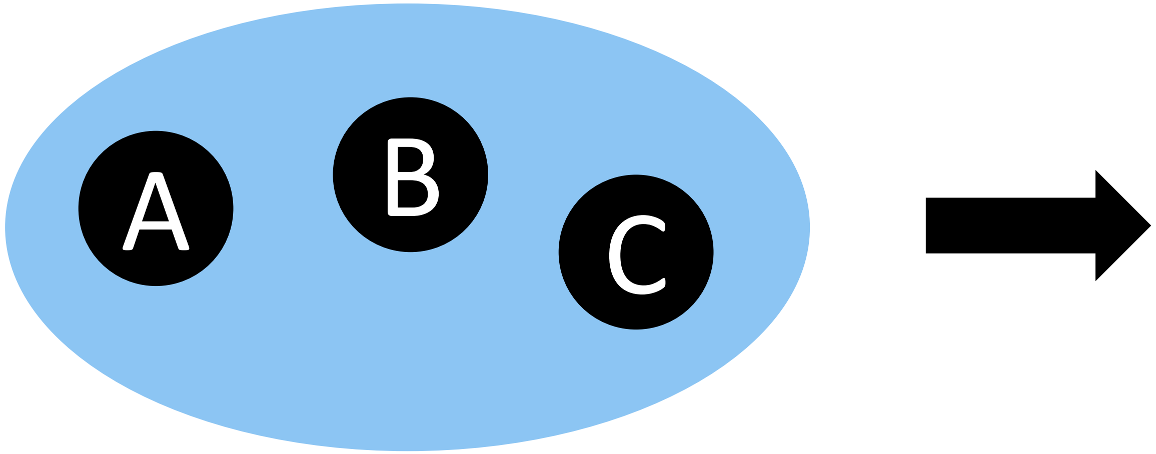

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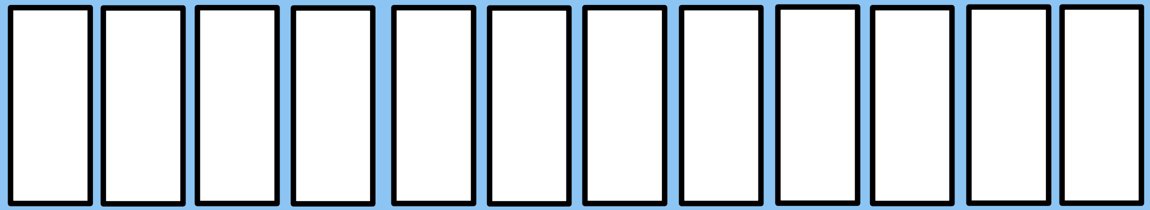

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h_1(A) = 3

h_2(A) = 5

Bloom Filters for Graph Mining

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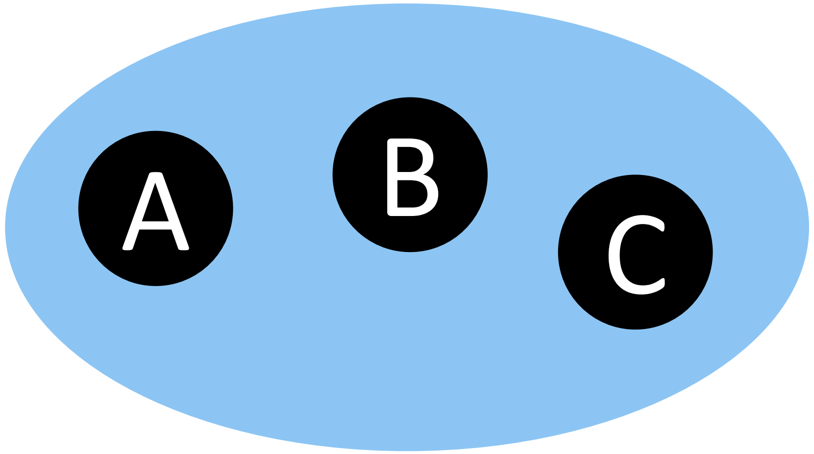

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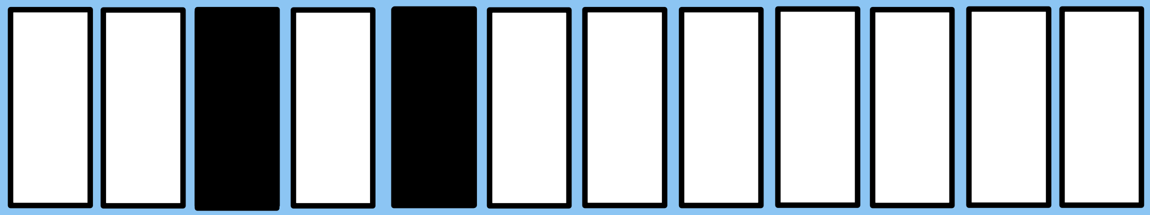

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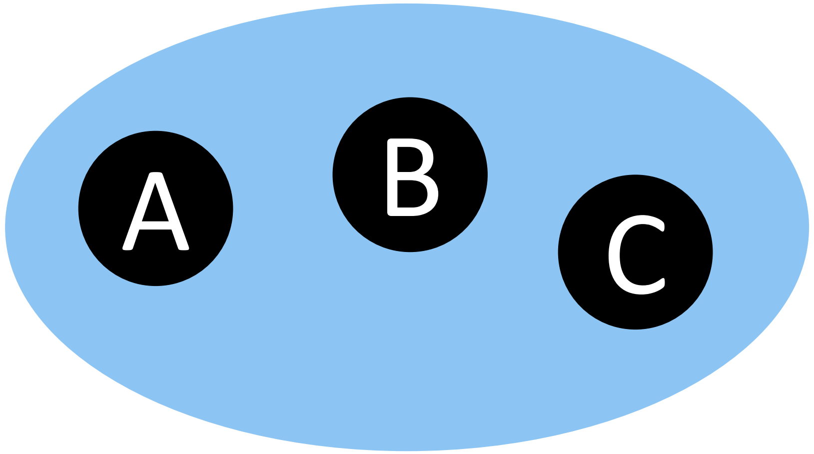

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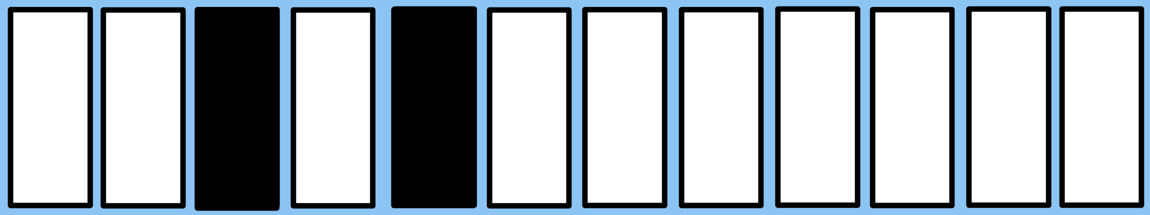

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Bloom Filters for Graph Mining

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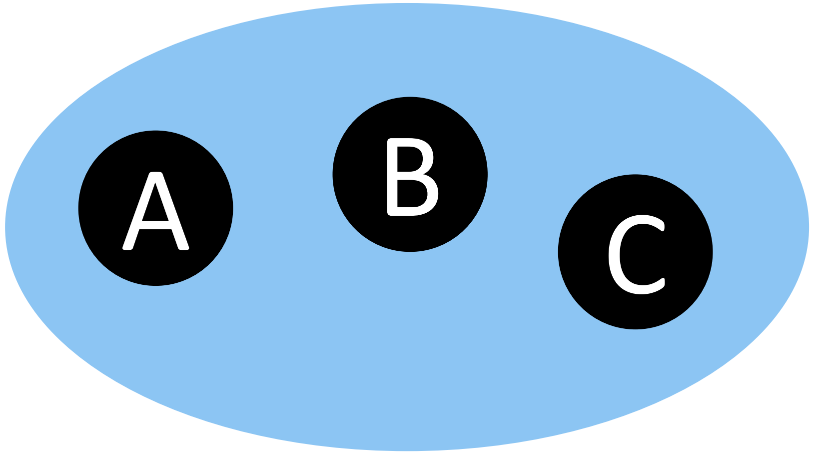

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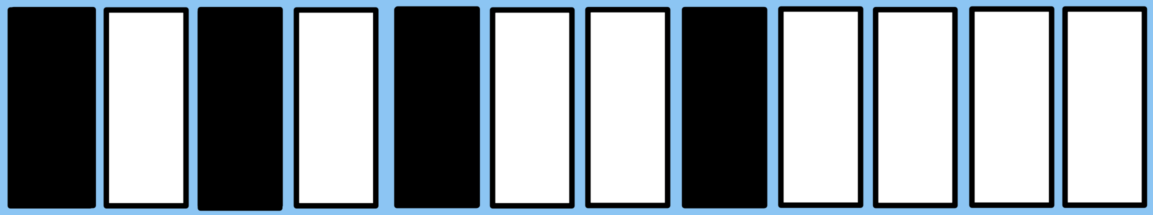
Bitvector of size B_X [bits] $B_X = 12$



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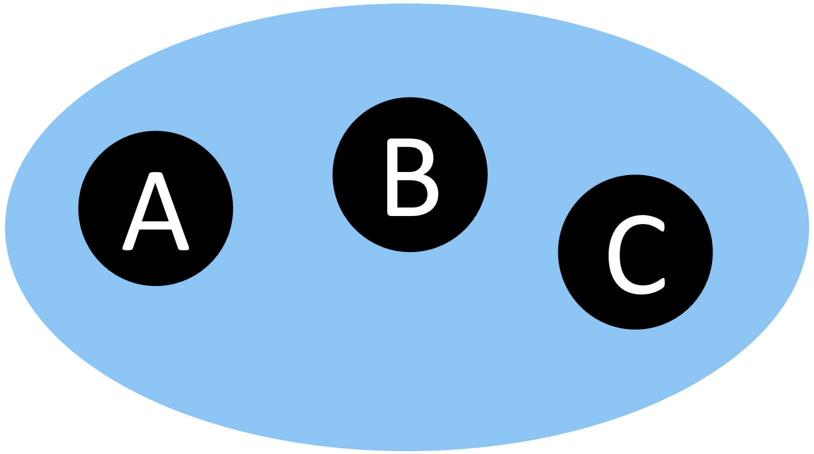

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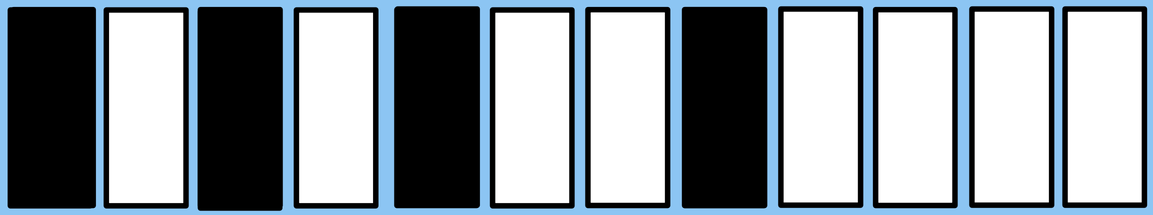

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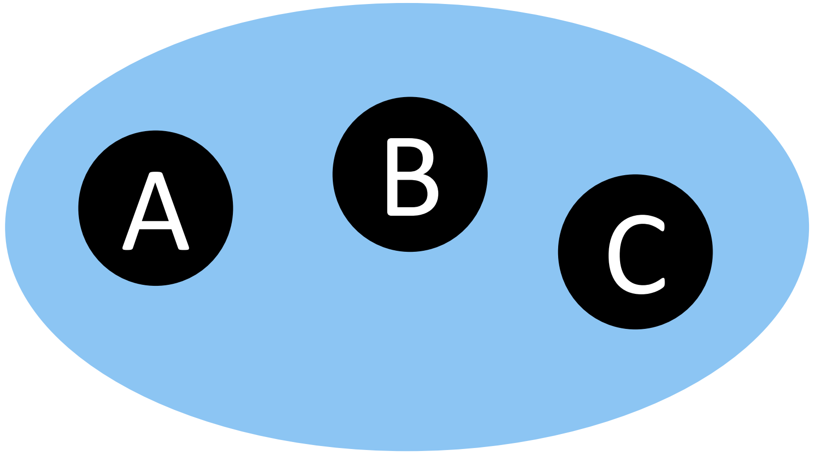

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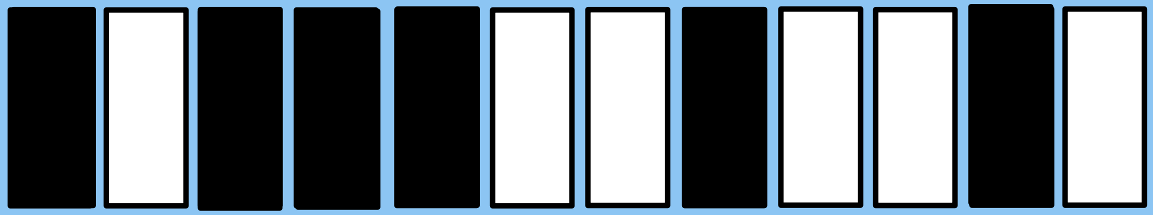

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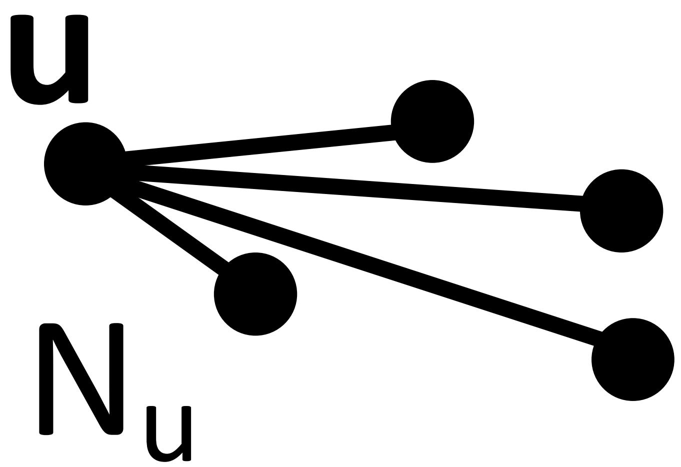
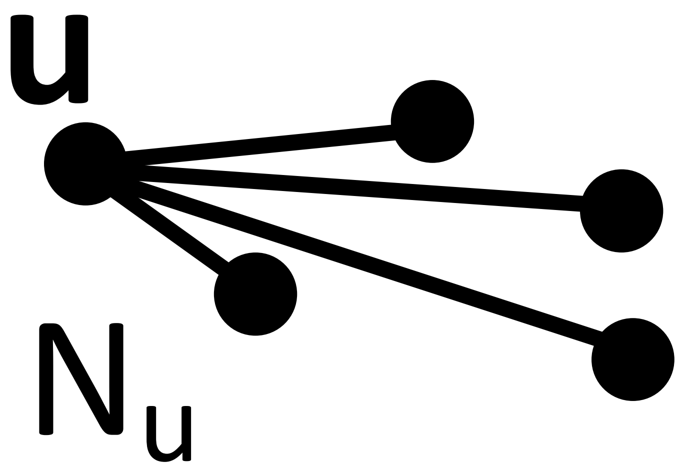


Bloom Filters for Graph Mining

Each neighborhood N_u is a set of vertices



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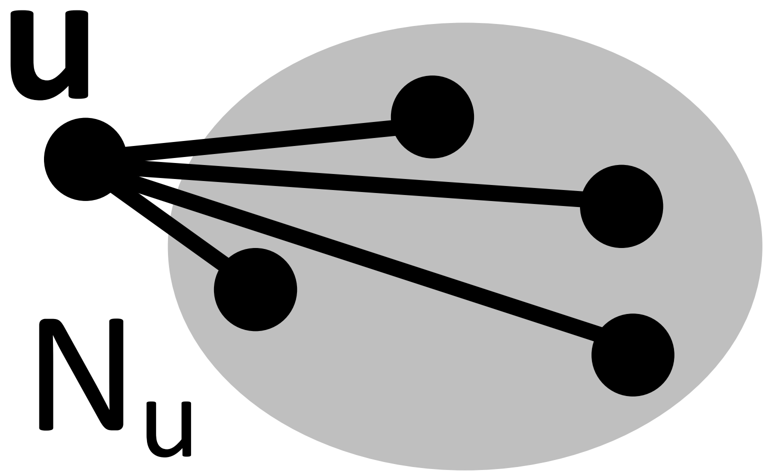

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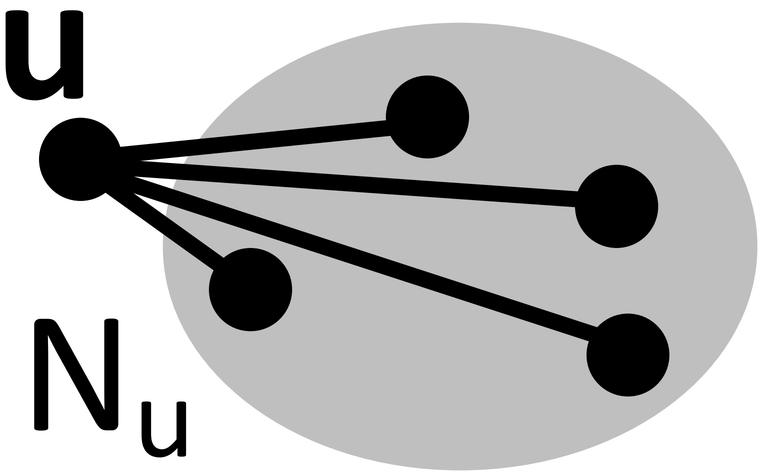
„Sketch" each N_u with a Bloom filter



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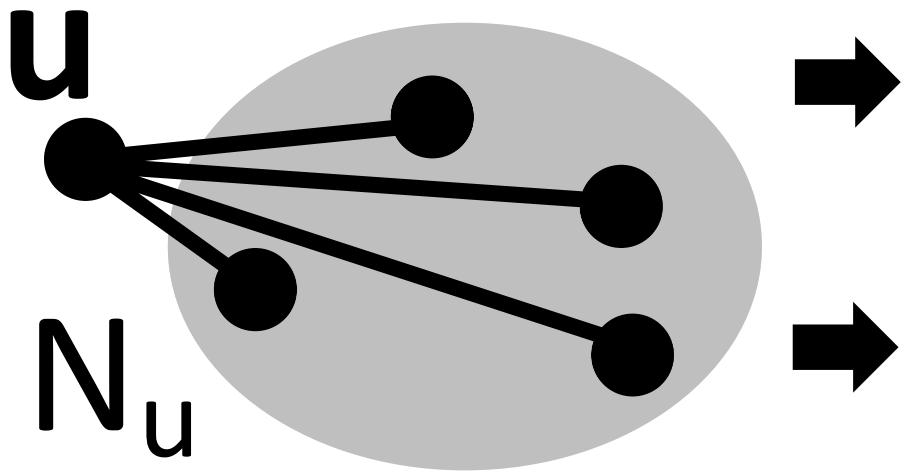

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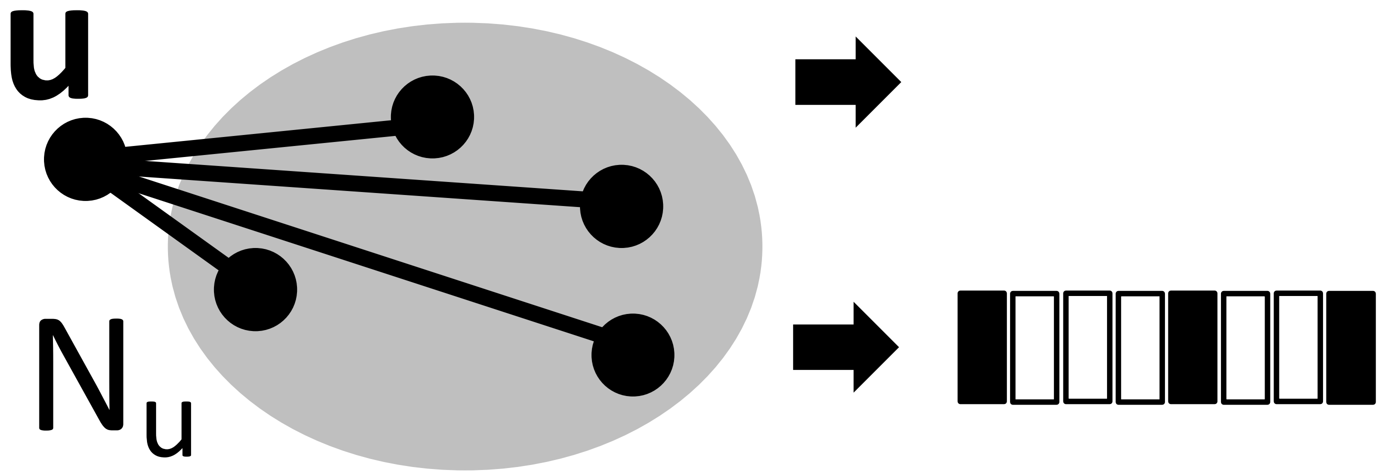

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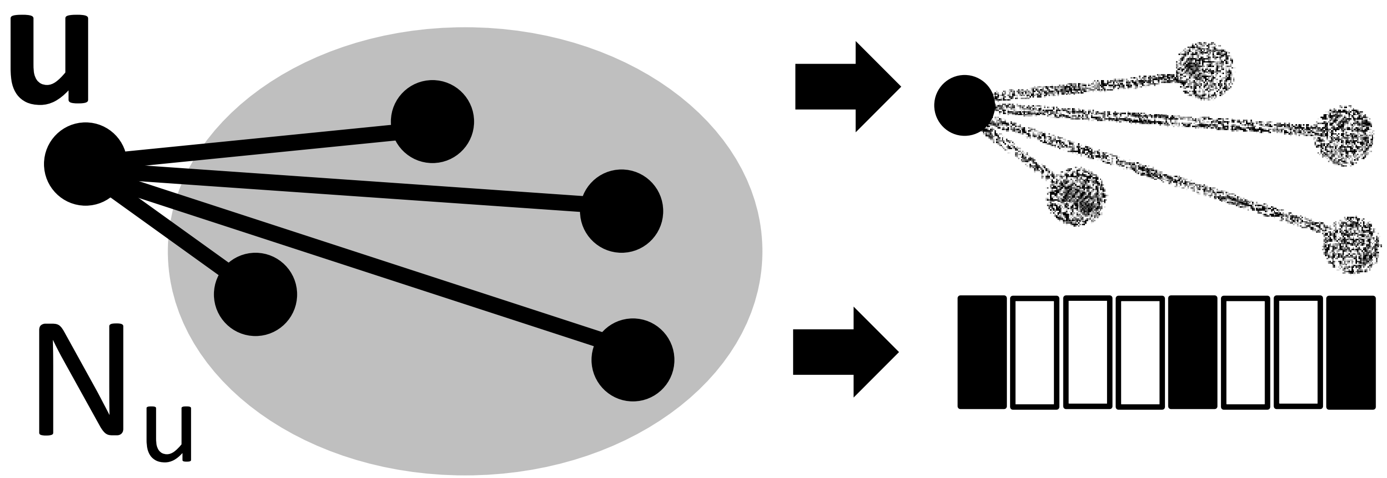

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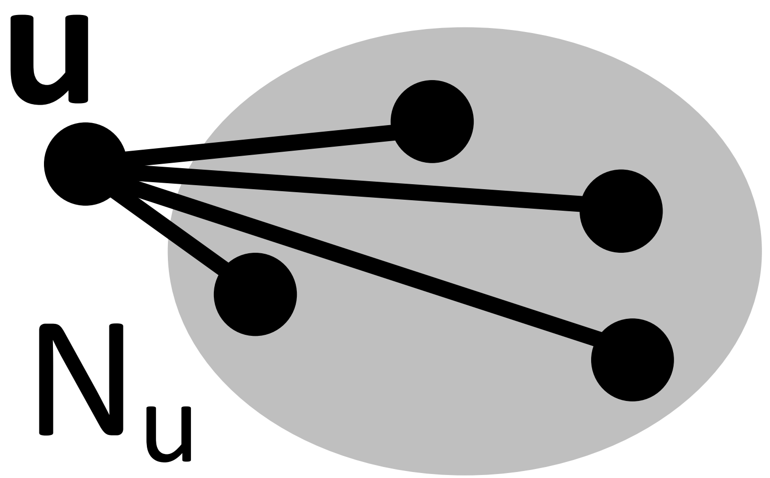

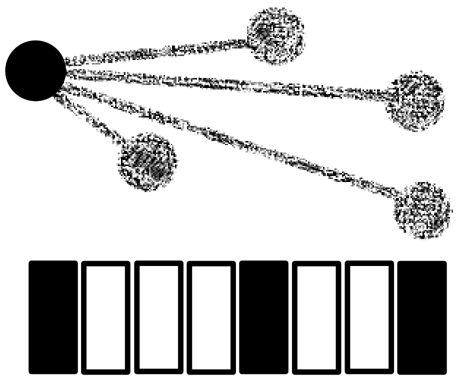

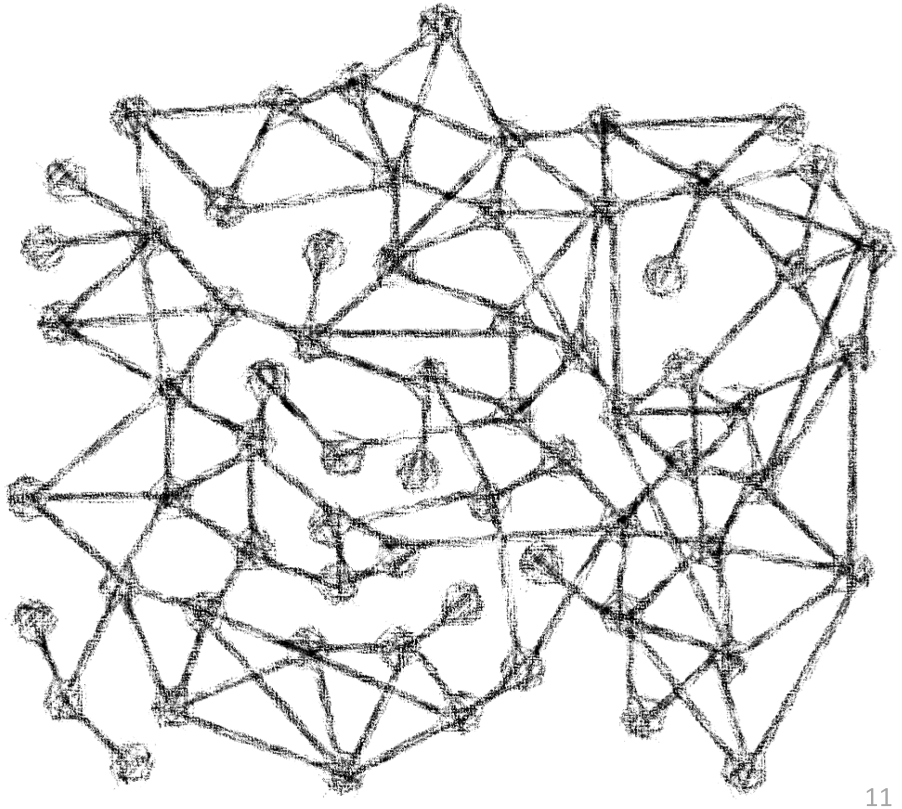

ProbGraph: Summary of Design

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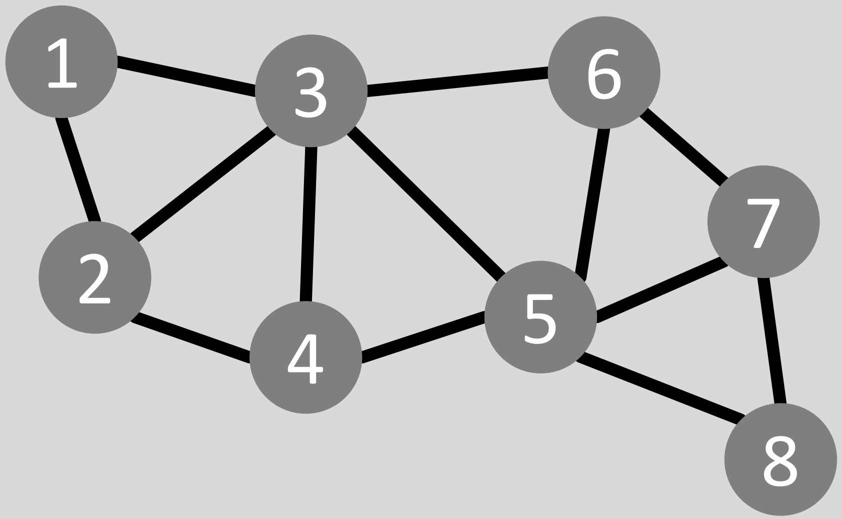
Input graph G



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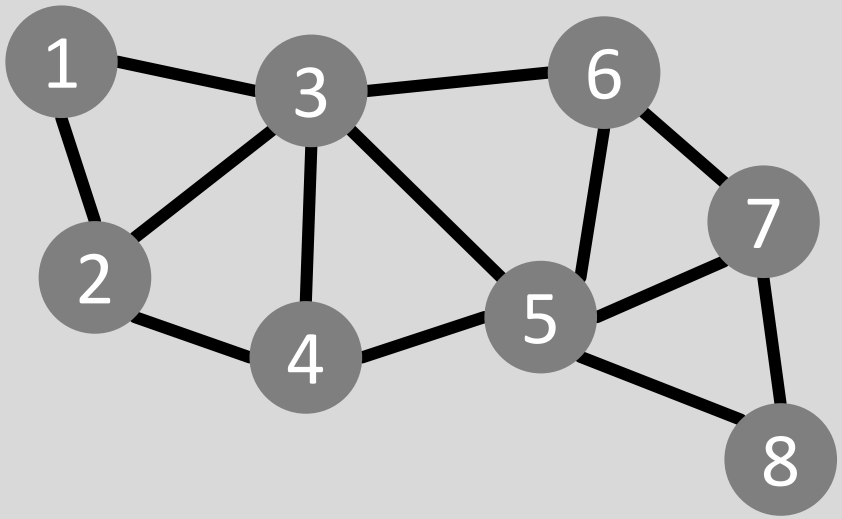

Standard graph representation (e.g., CSR)

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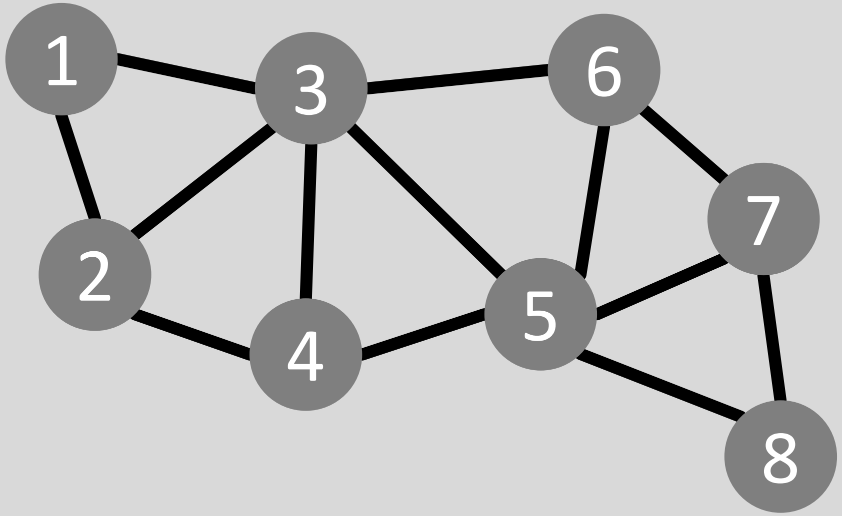

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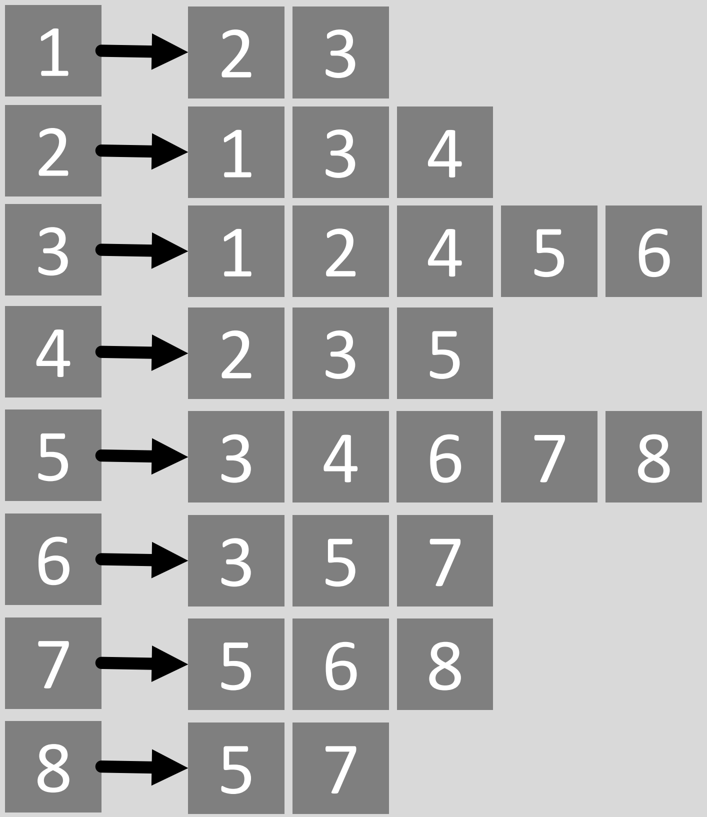

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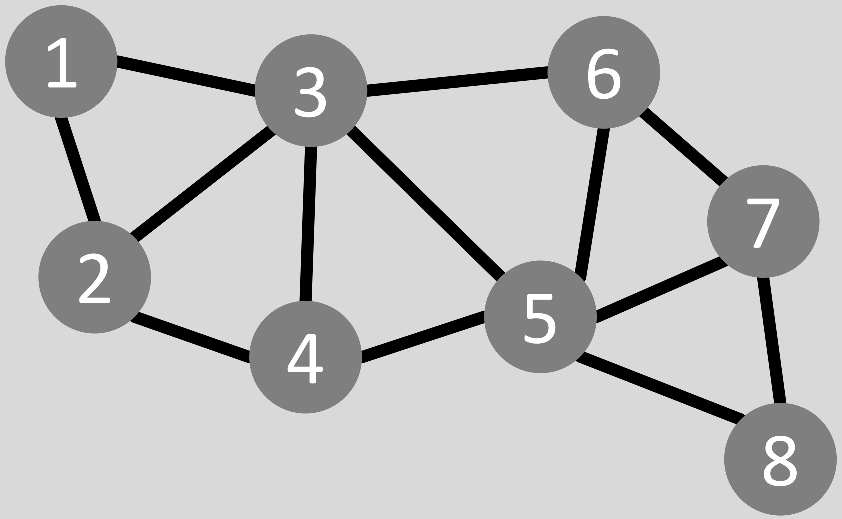

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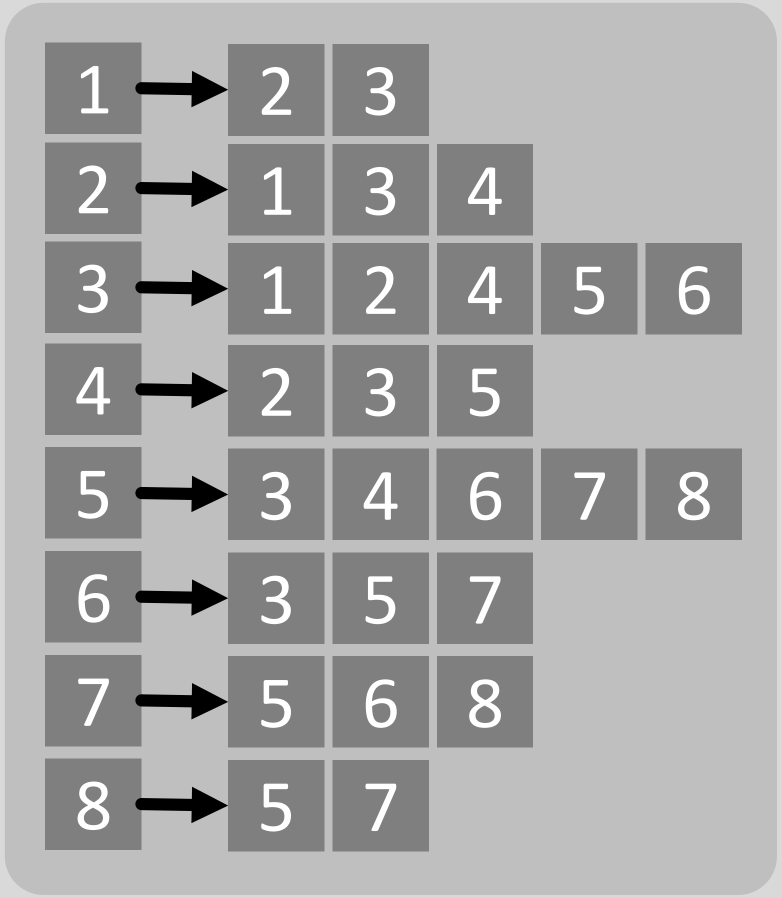

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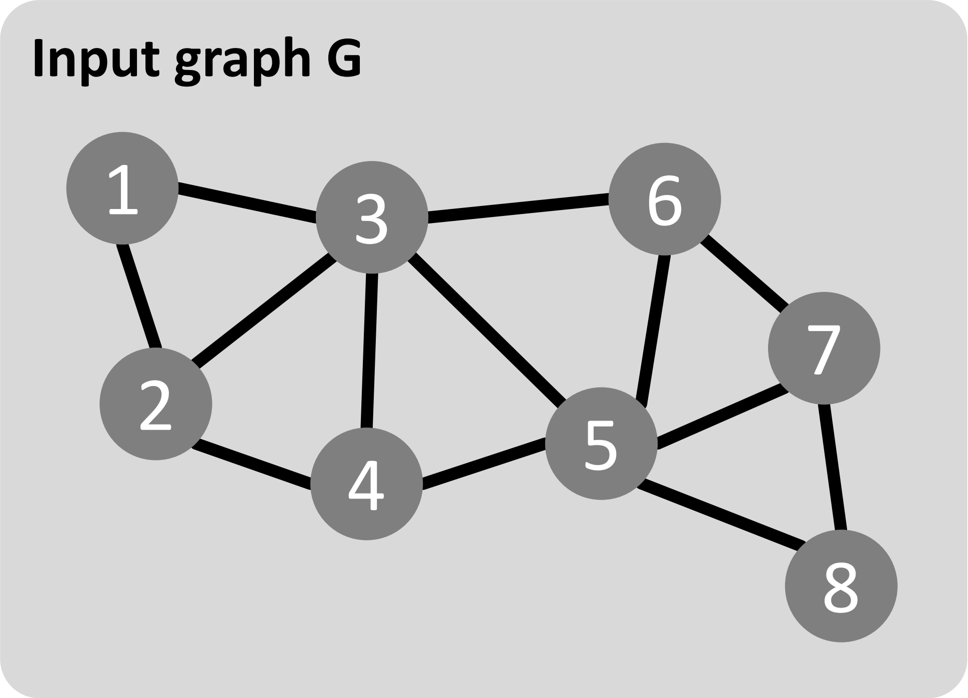

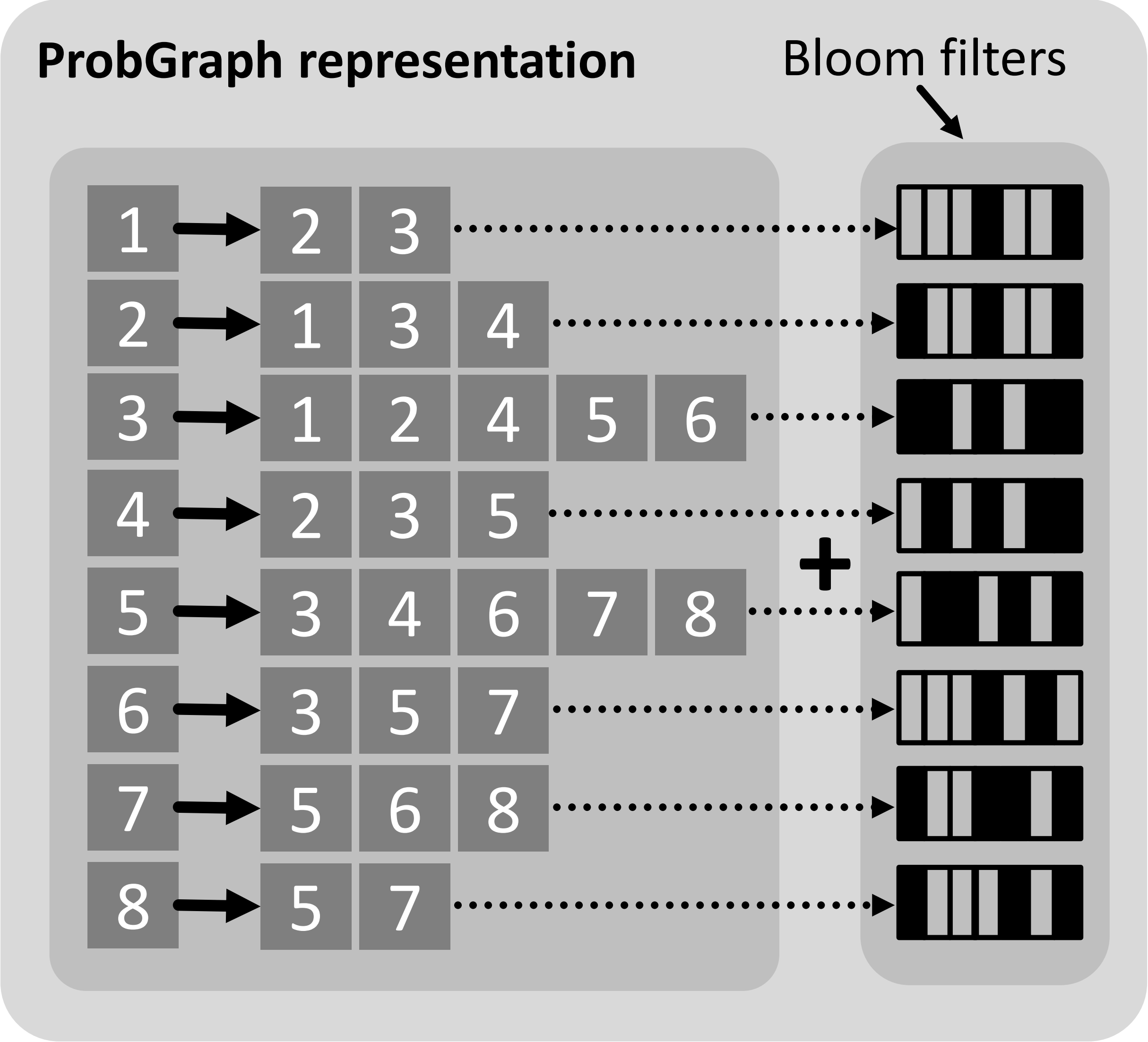

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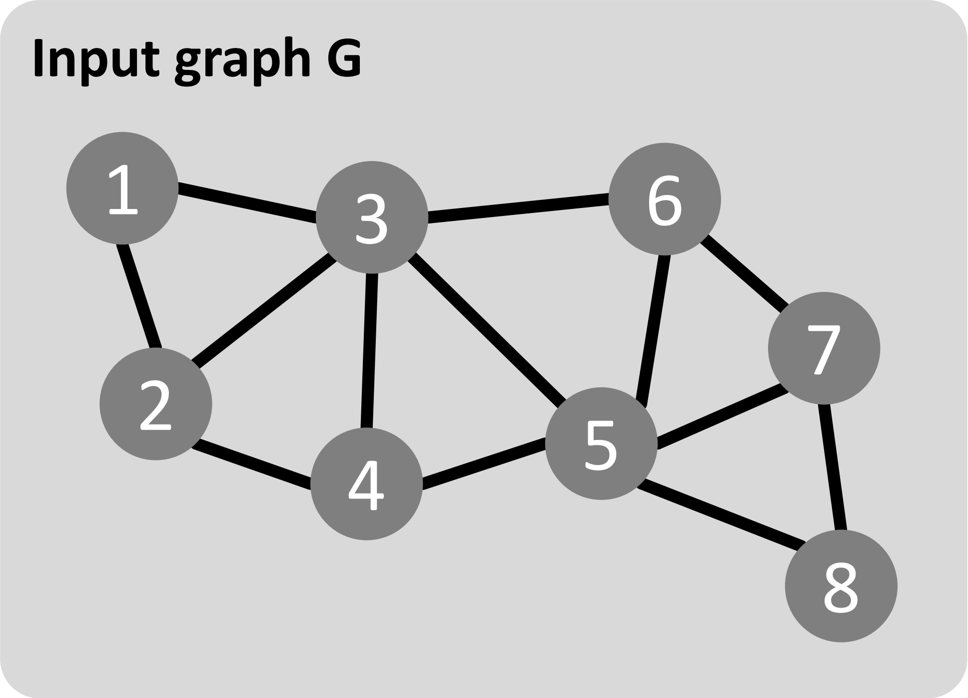

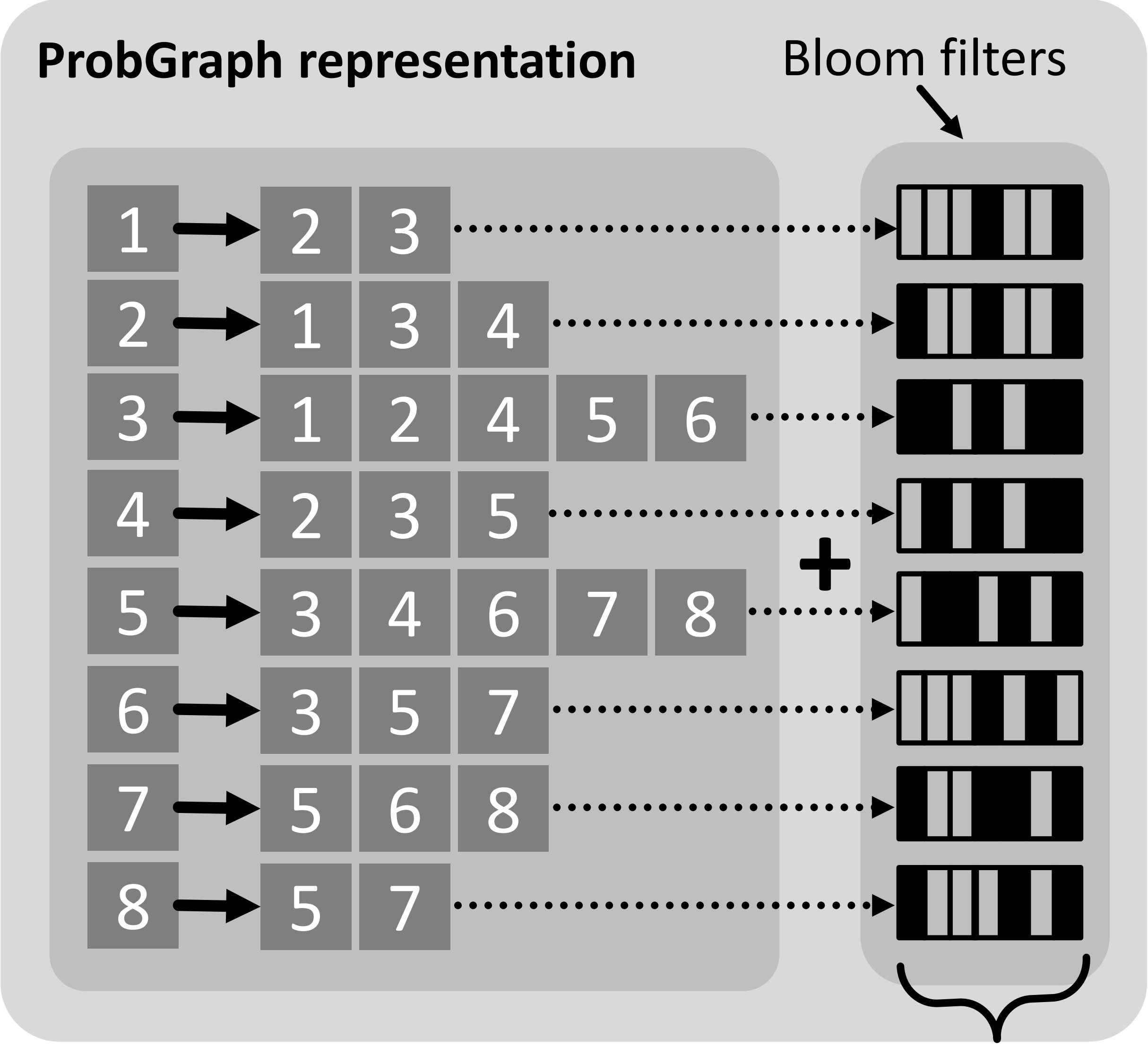

Larger B_X : more accuracy & more storage required. **Lower B_X** : vice versa. → **B_X** [bits]

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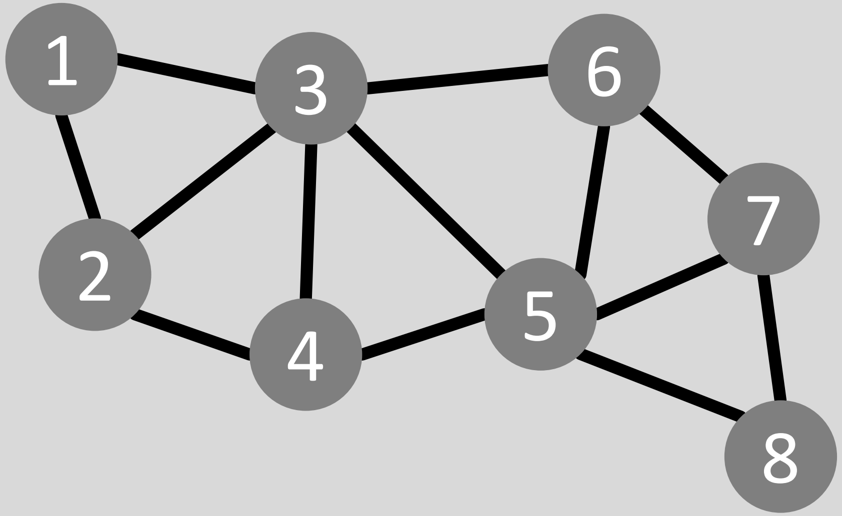

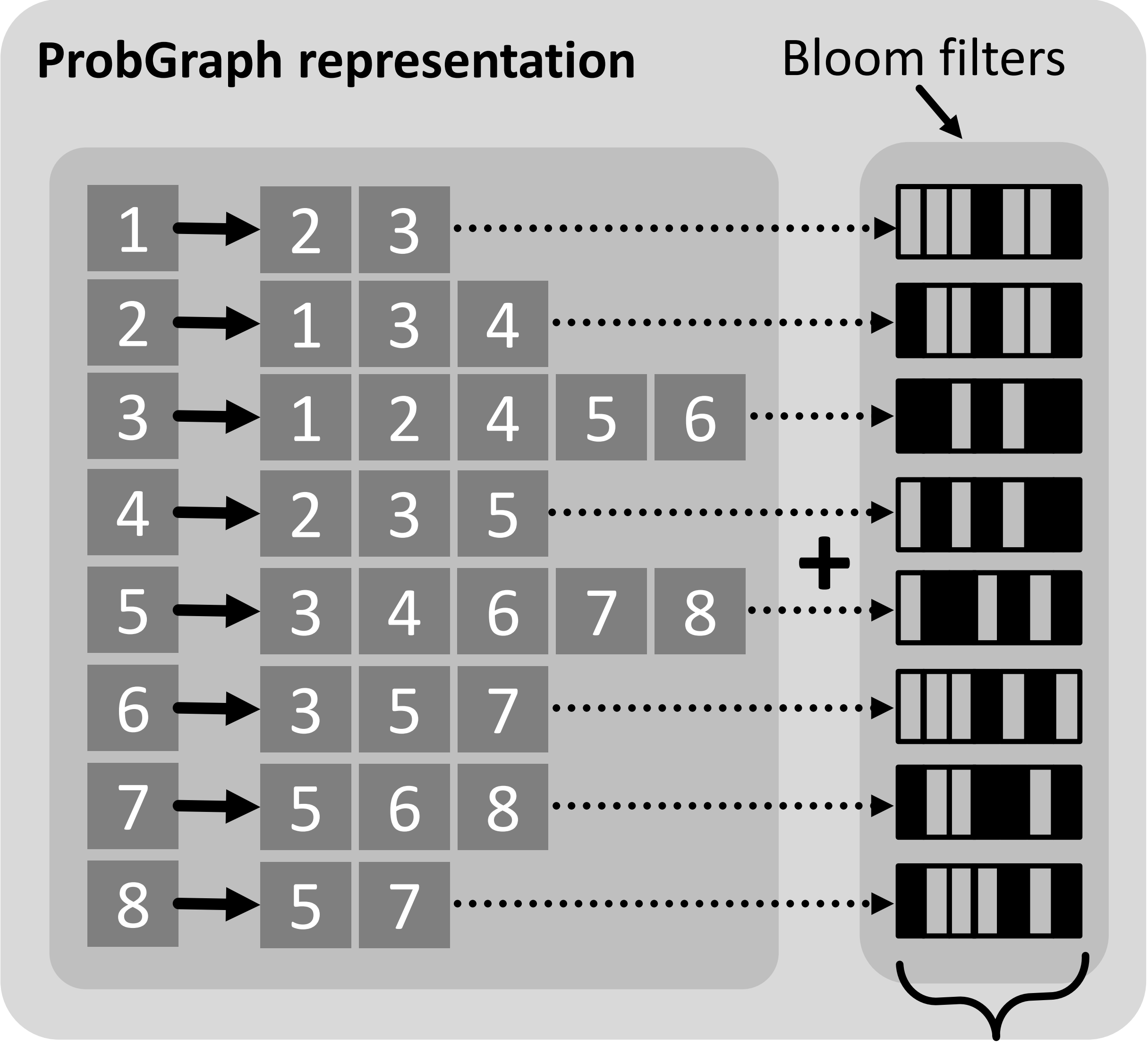

B_X is often small → little storage

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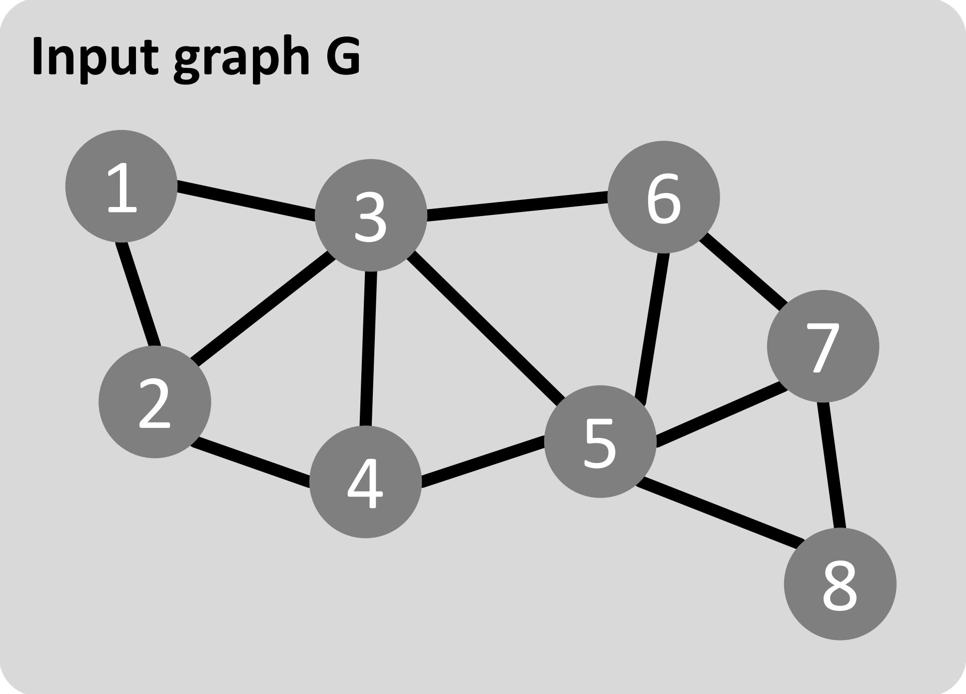

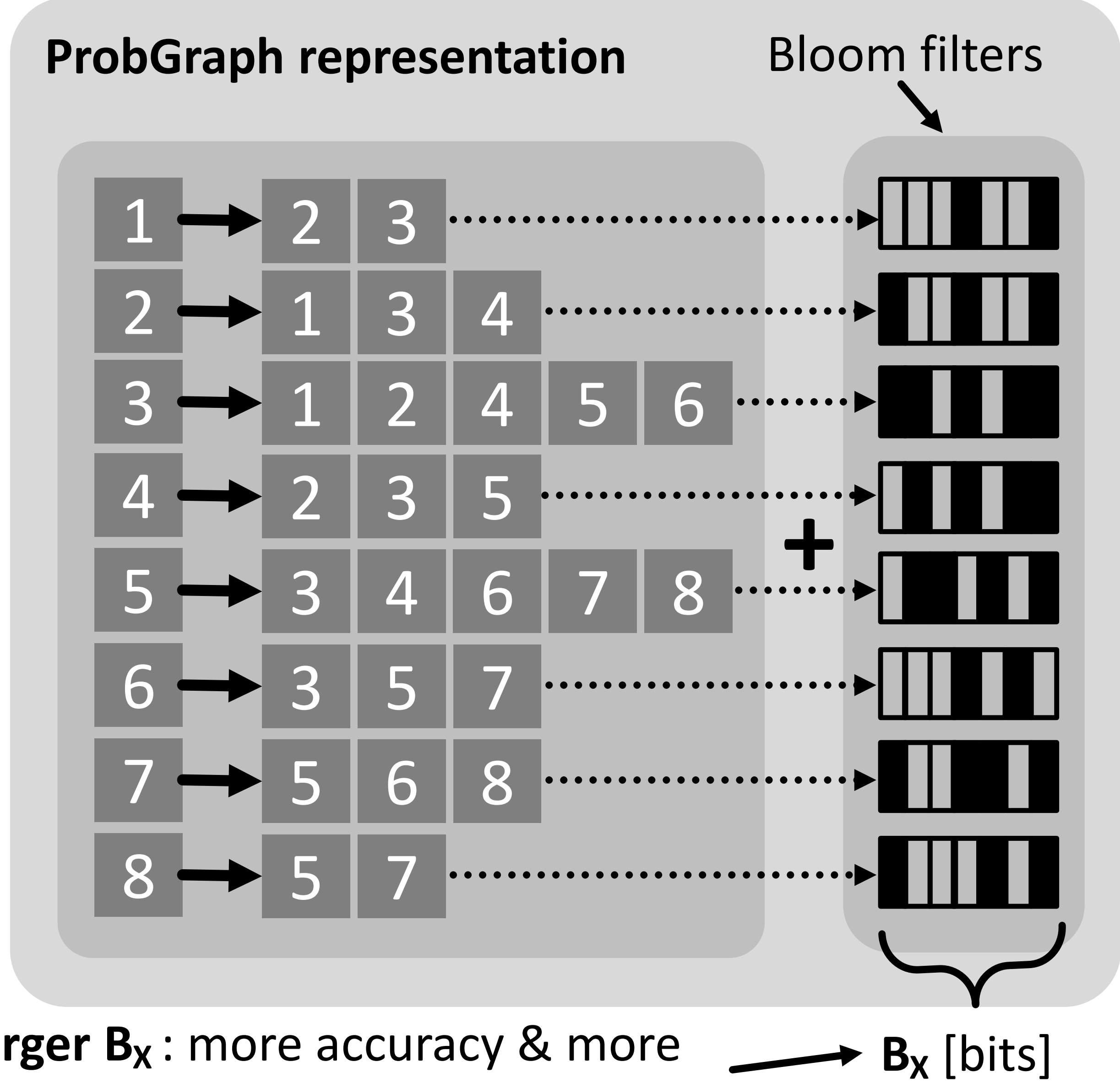

B_X is often small → little storage

BFs have the same size → great load balancing

Larger B_X : more accuracy & more storage required. **Lower B_X** : vice versa.

How does our idea compare to other Bloom filter use cases?

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Traditional BF use case: presence tracking

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Data stored somewhere

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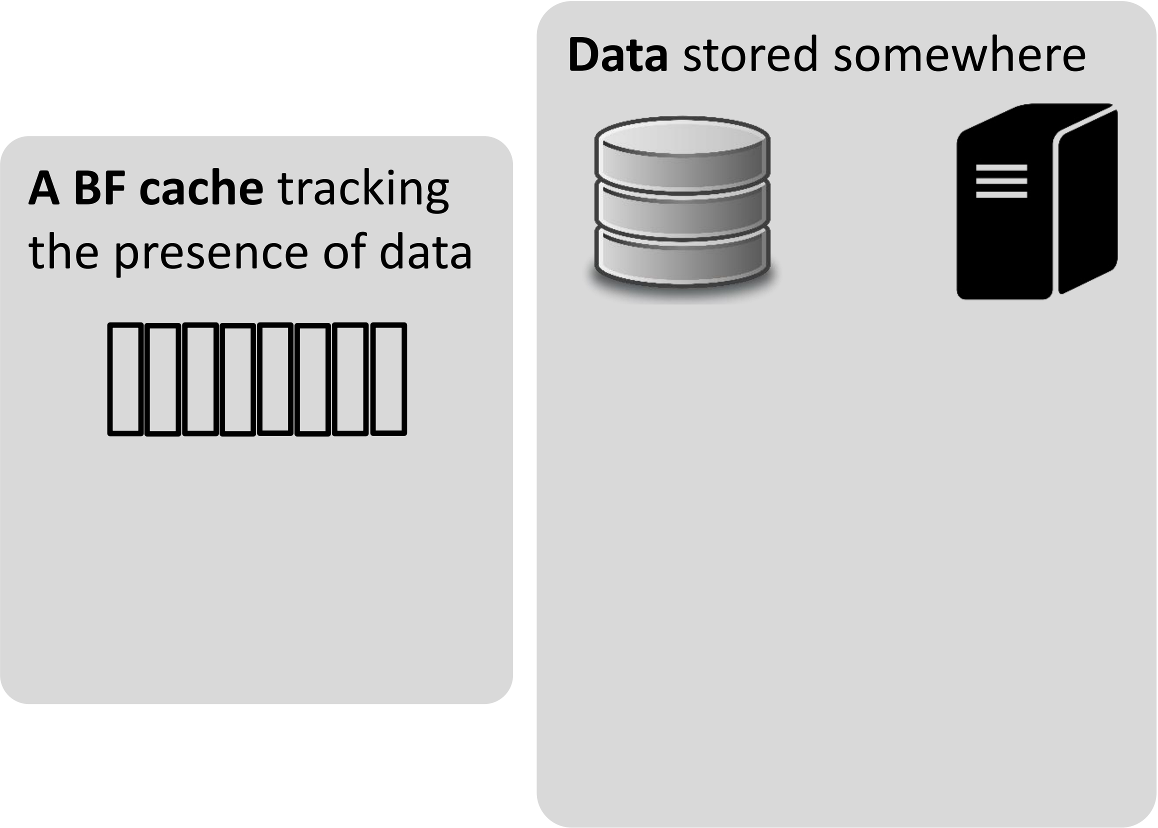

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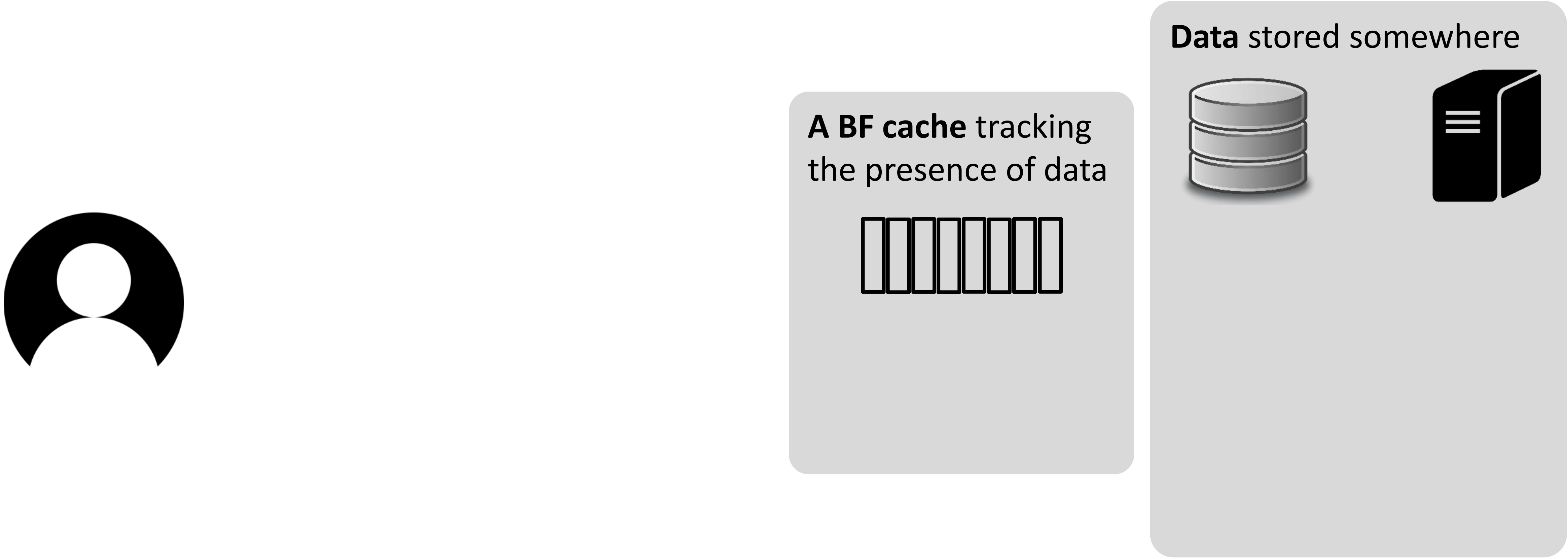

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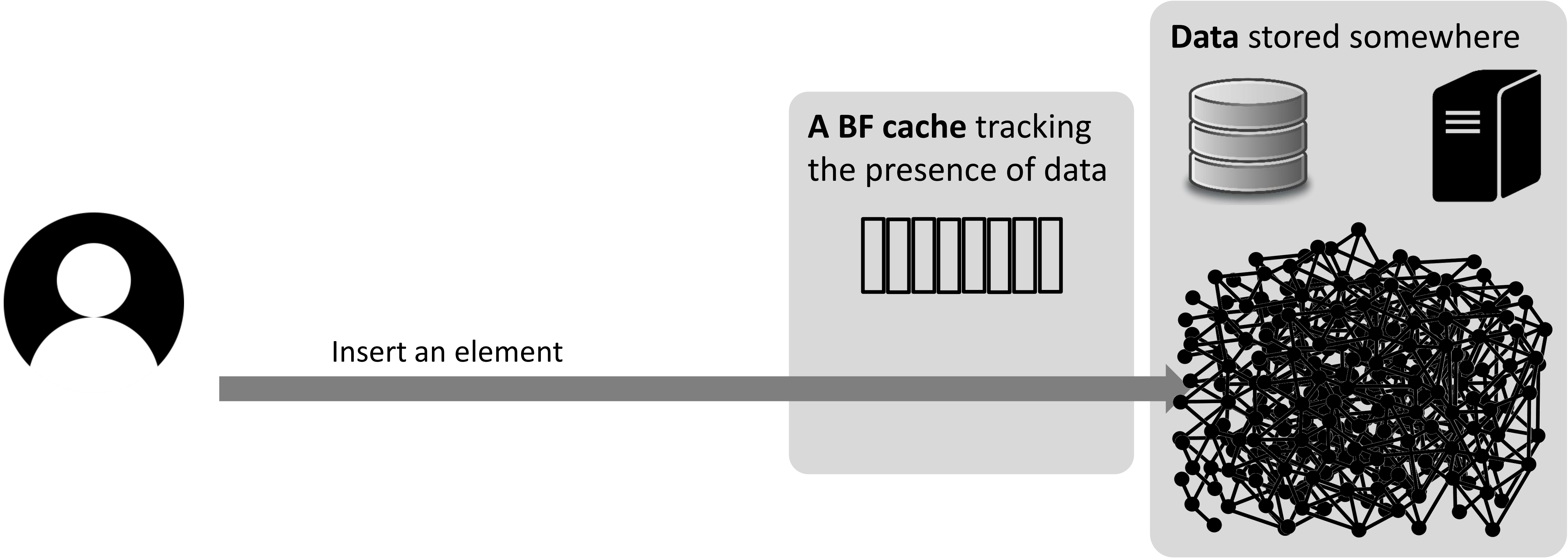

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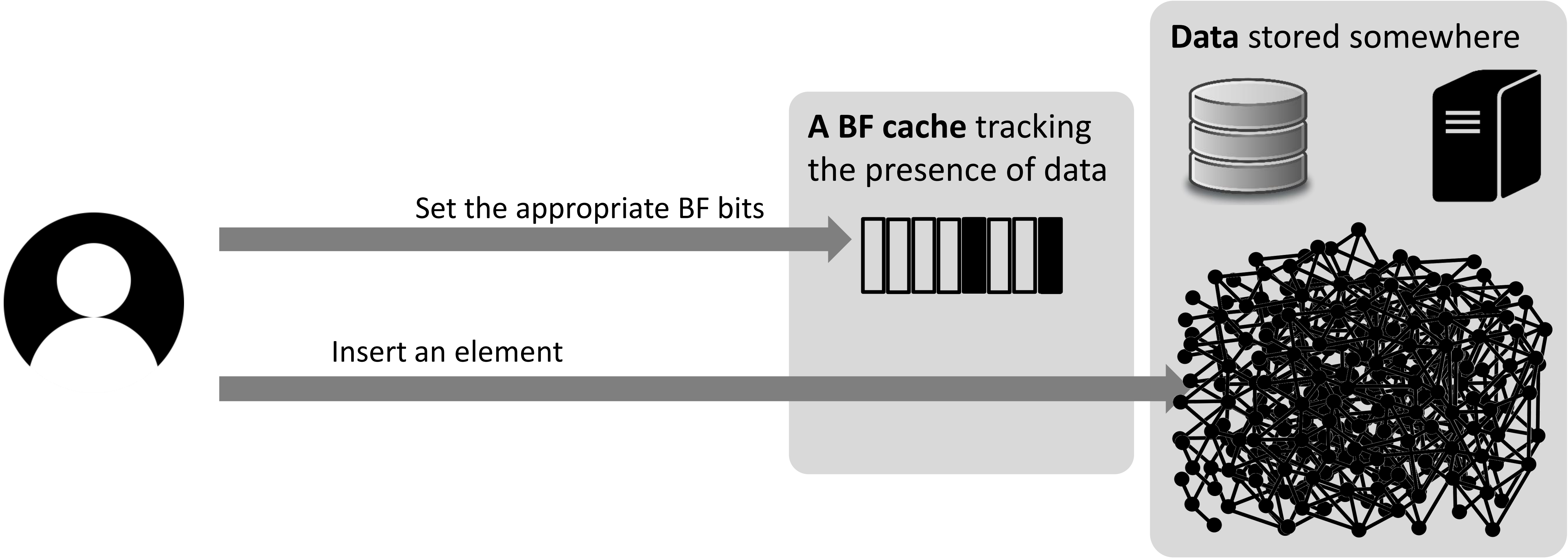

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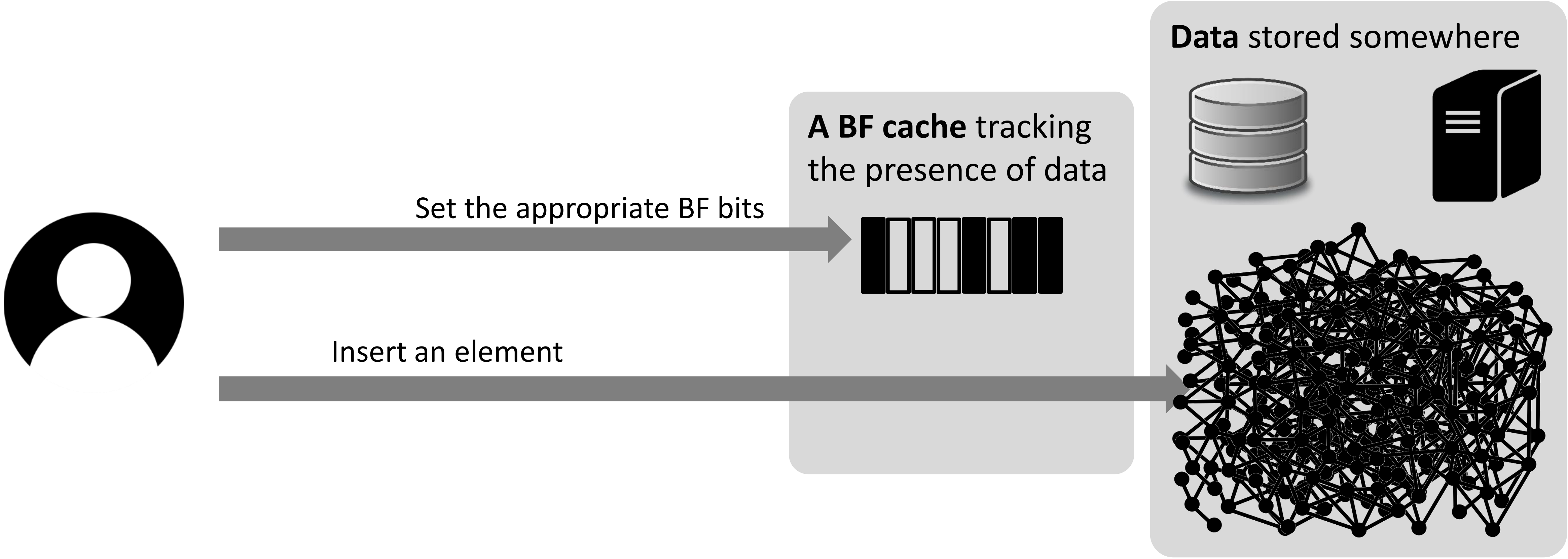

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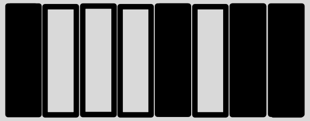
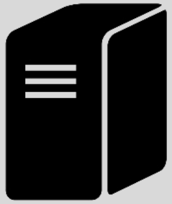
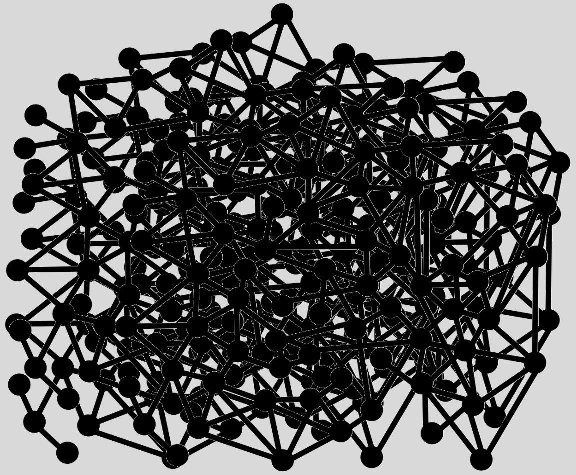
A BF cache tracking the presence of data



Data stored somewhere





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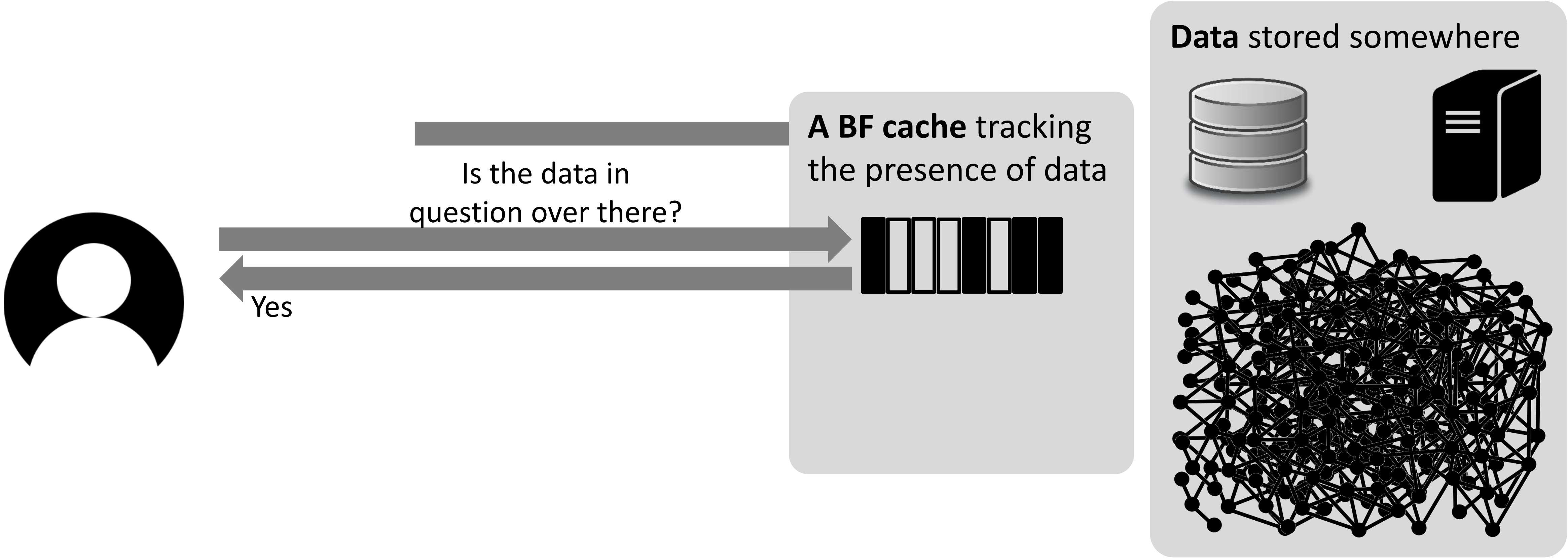

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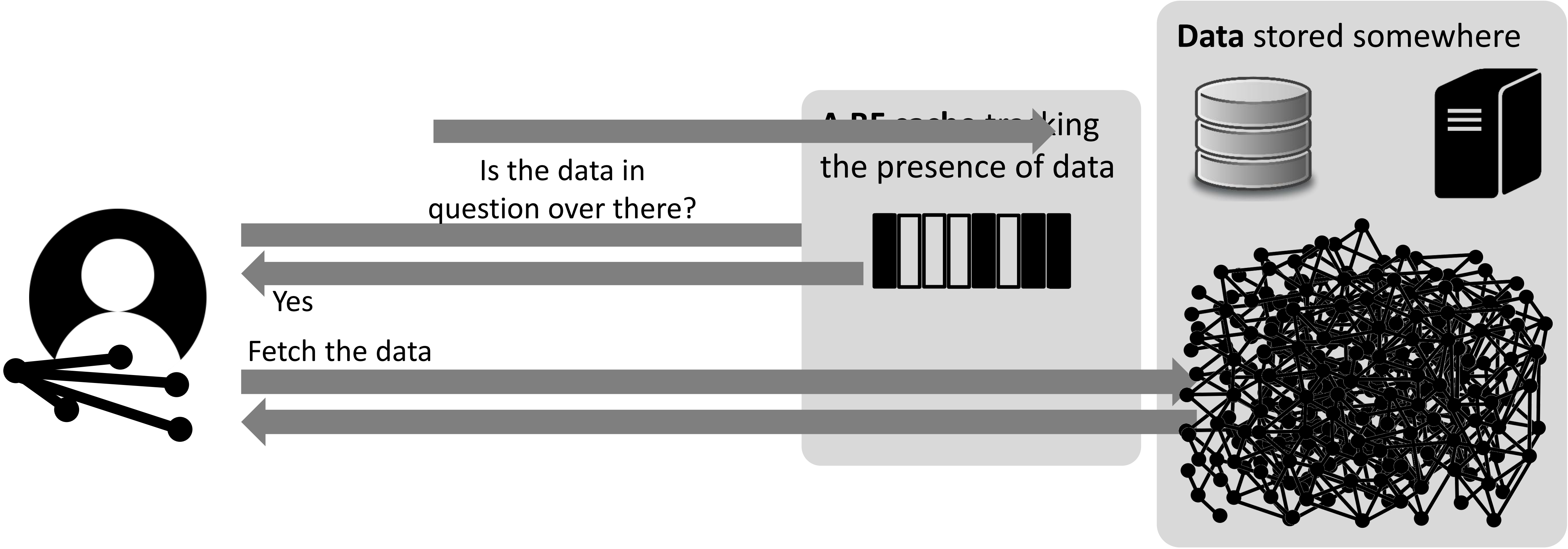

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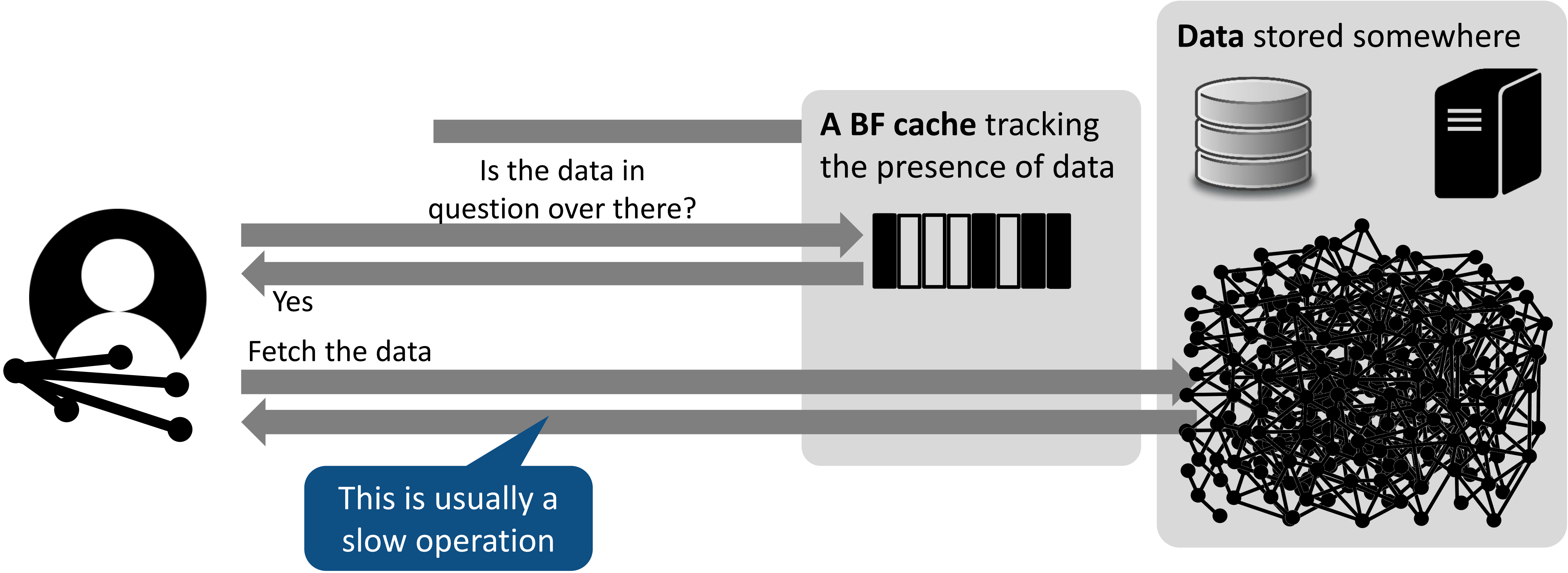

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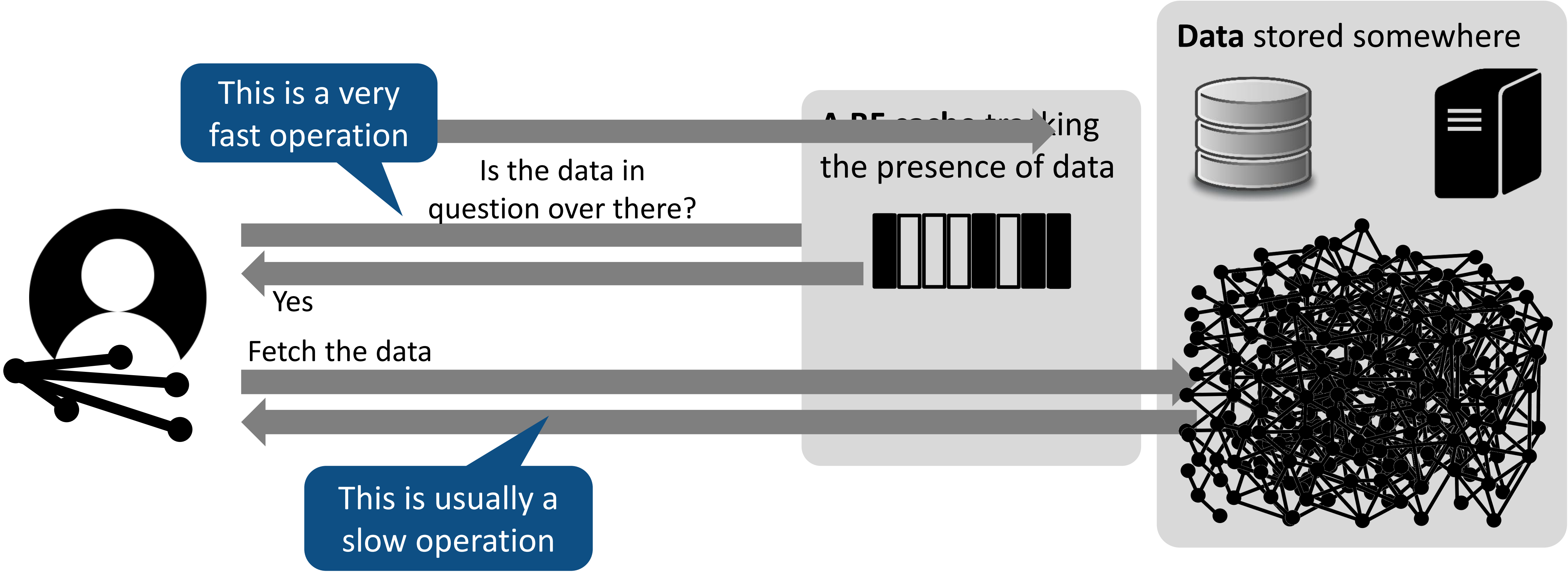
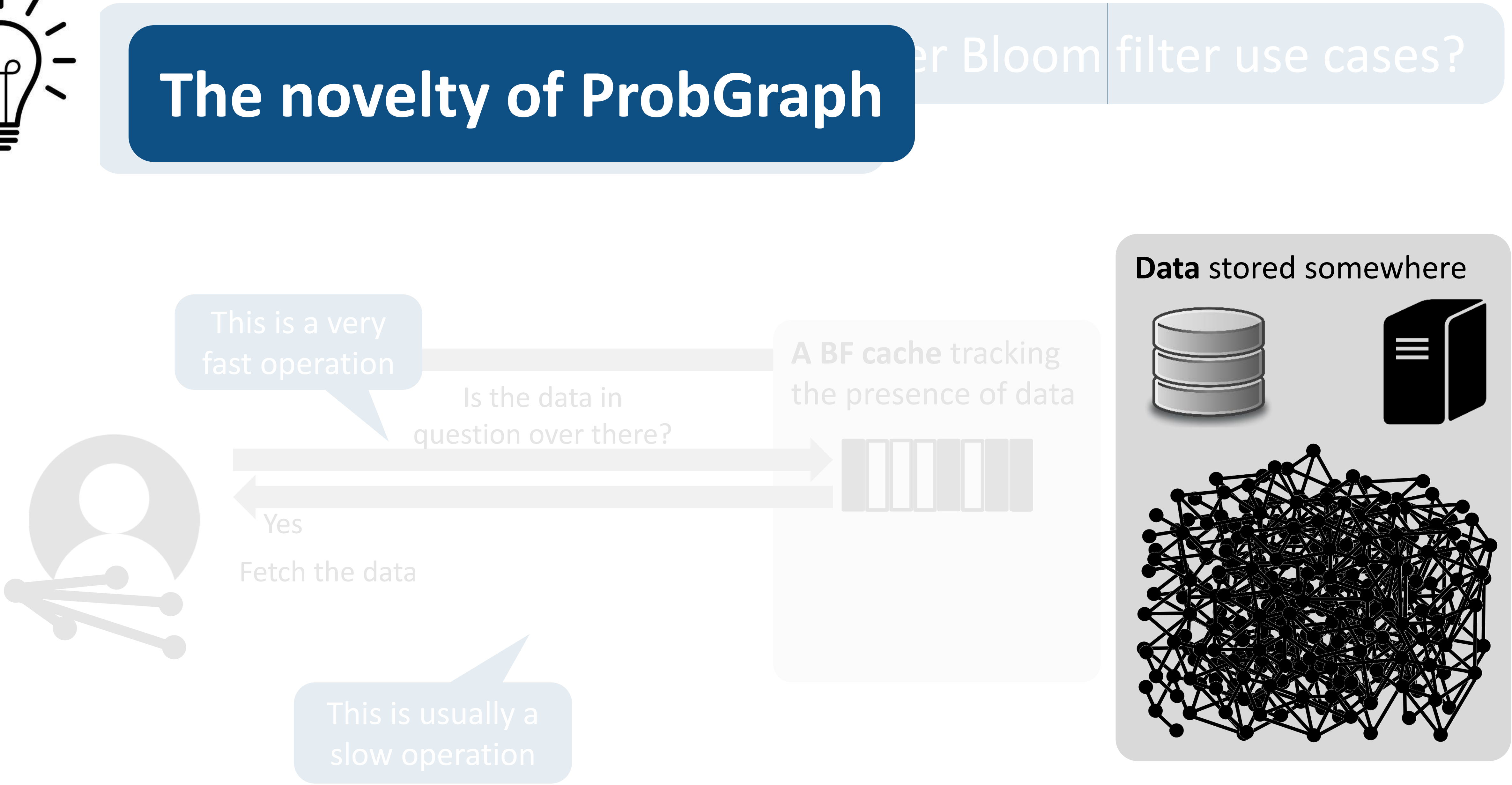


The novelty of ProbGraph



The novelty of ProbGraph

...er Bloom filter use cases?

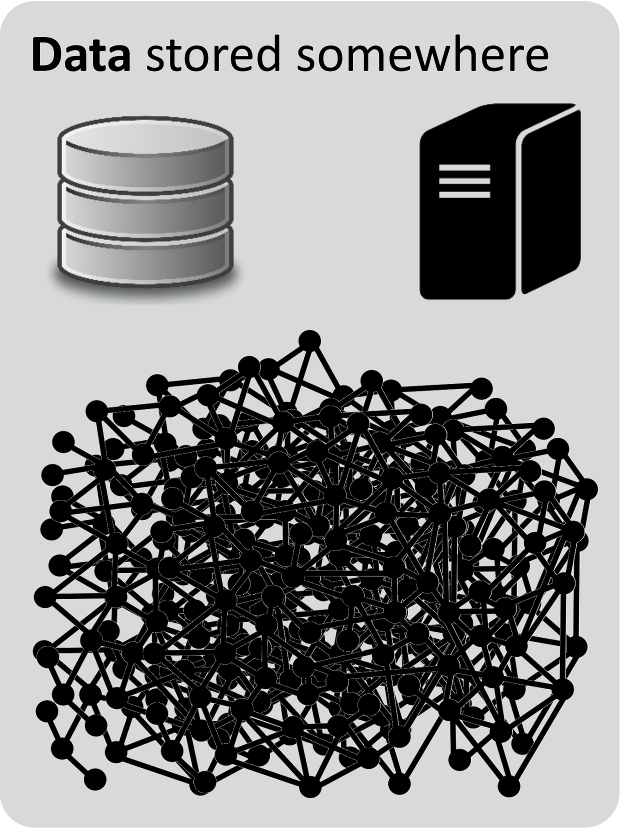
We use BFs as a sketch of <u>the actual dataset</u>

...BF cache tracking
...e presence of data

Yes

Fetch the data

This is usually a slow operation



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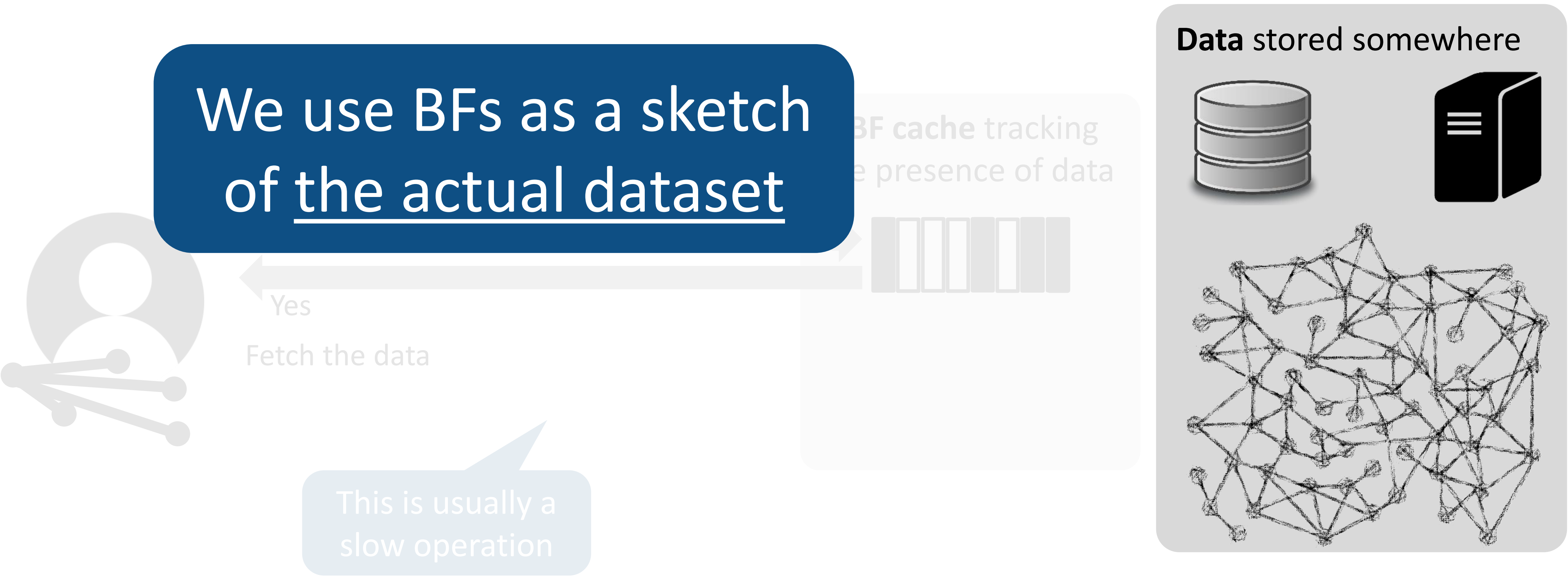
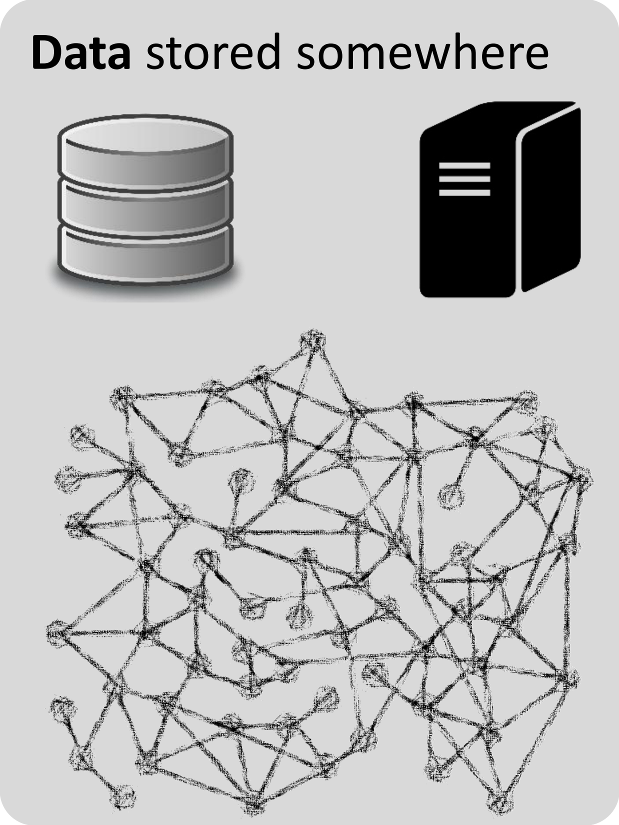


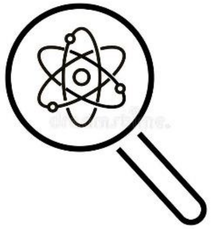
The novelty of ProbGraph

We use BFs as a sketch of the actual dataset

How do we exactly use these sketches to benefit graph mining?



Observation: Set Intersection Cardinality is Prevalent in Graph Mining



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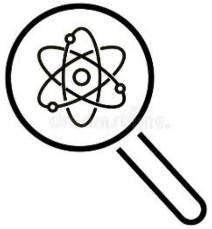

$$|X \cap Y|$$

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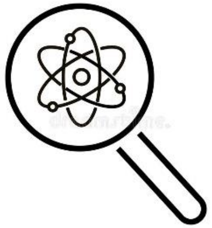

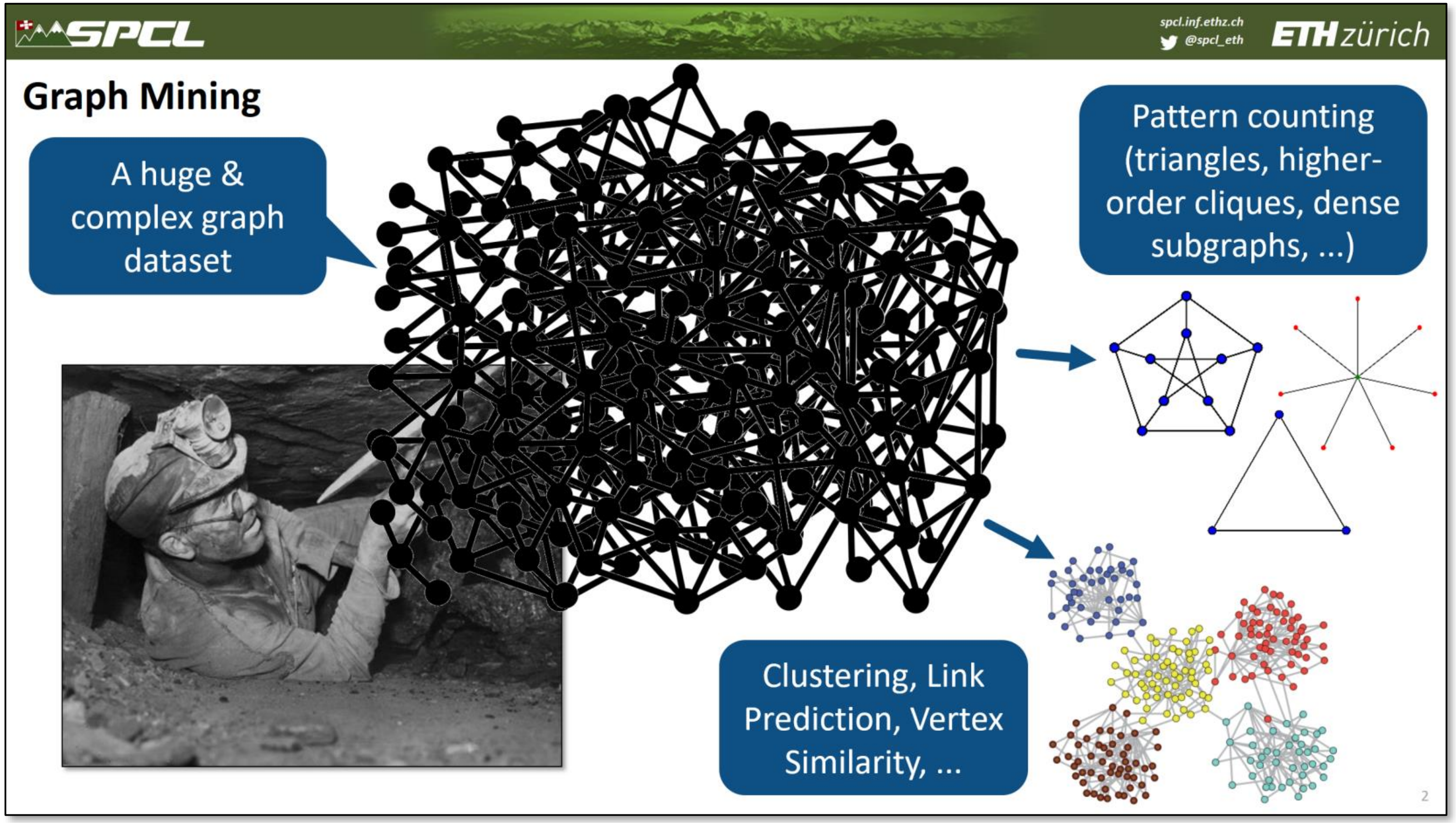

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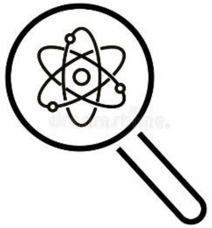

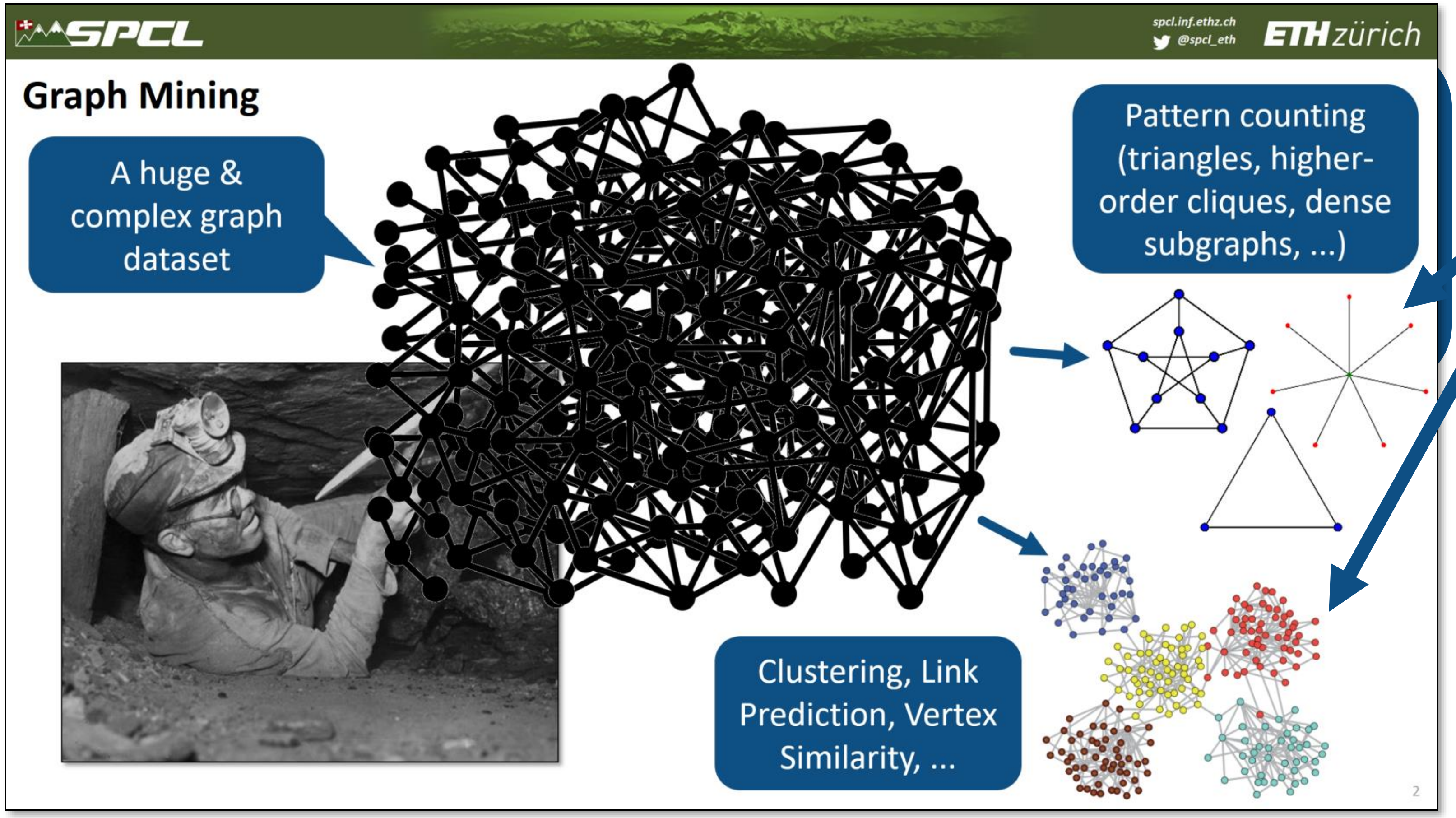

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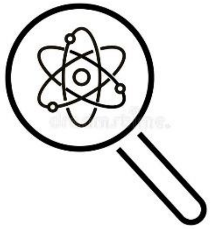
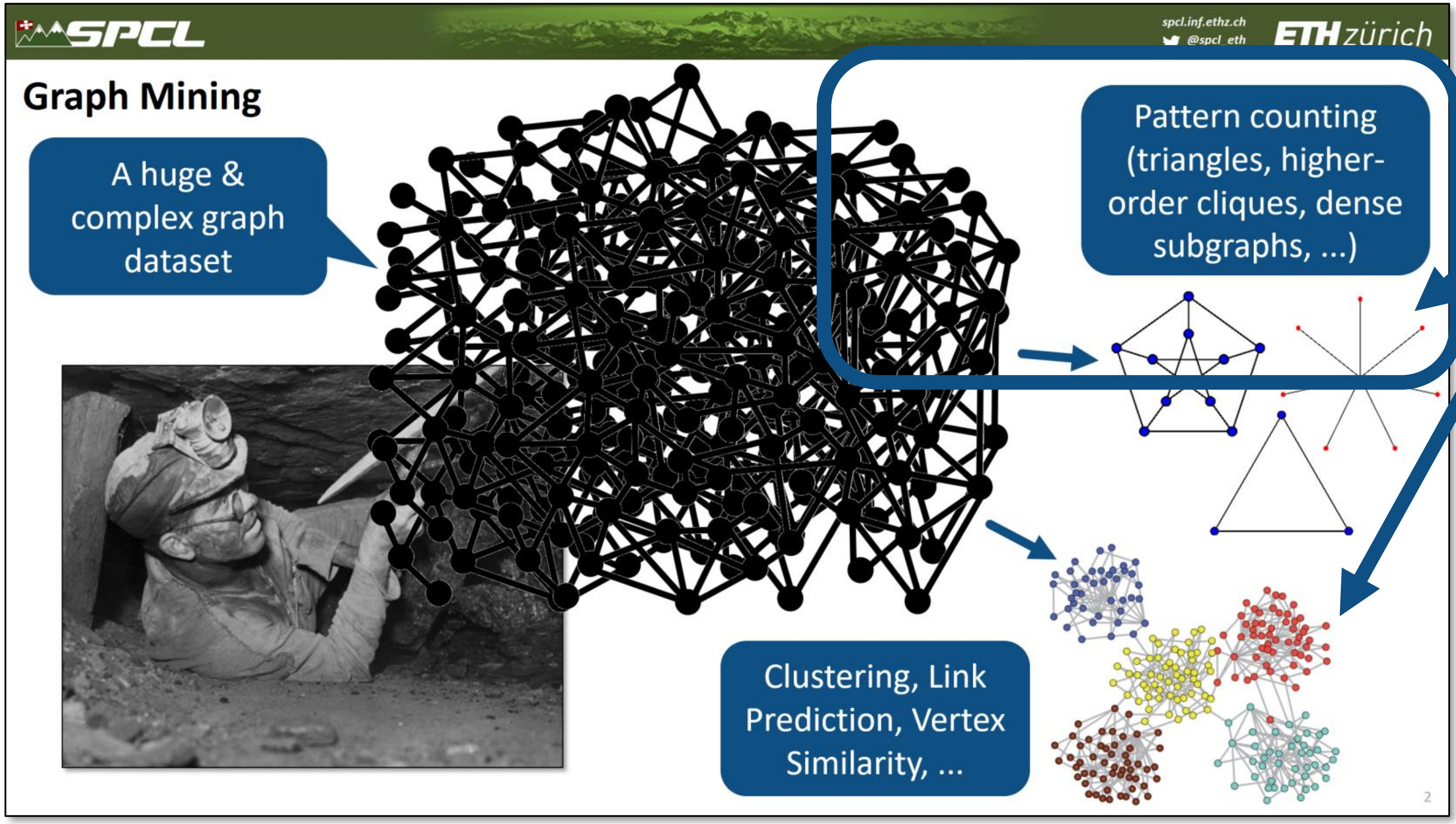


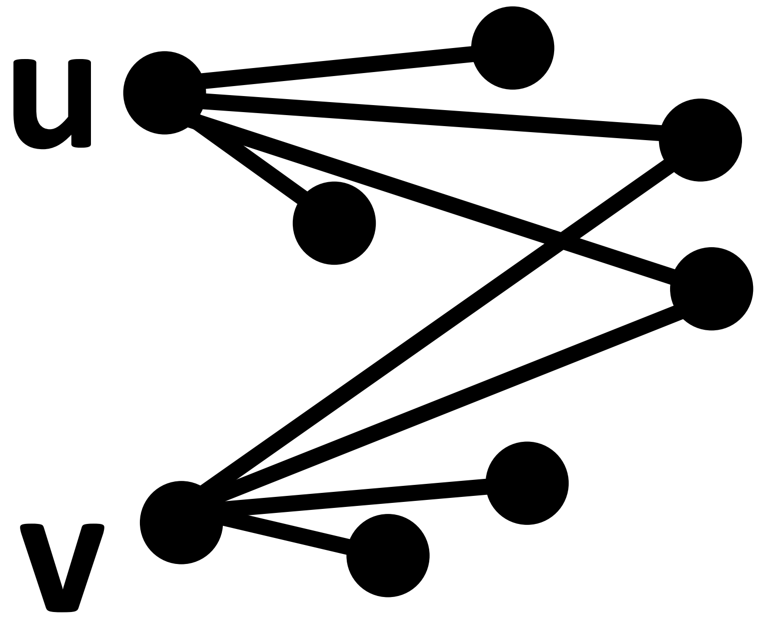


$|X \cap Y|$

We greatly accelerate $|X \cap Y|$ with BFs

ProbGraph key idea, continued

ProbGraph key idea, continued



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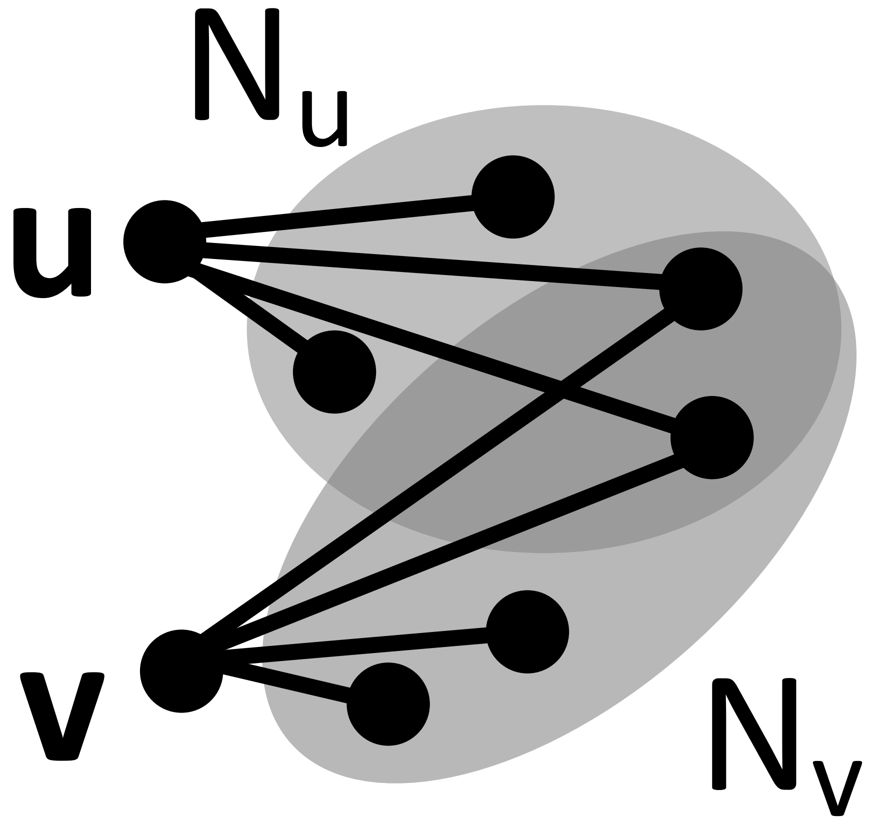

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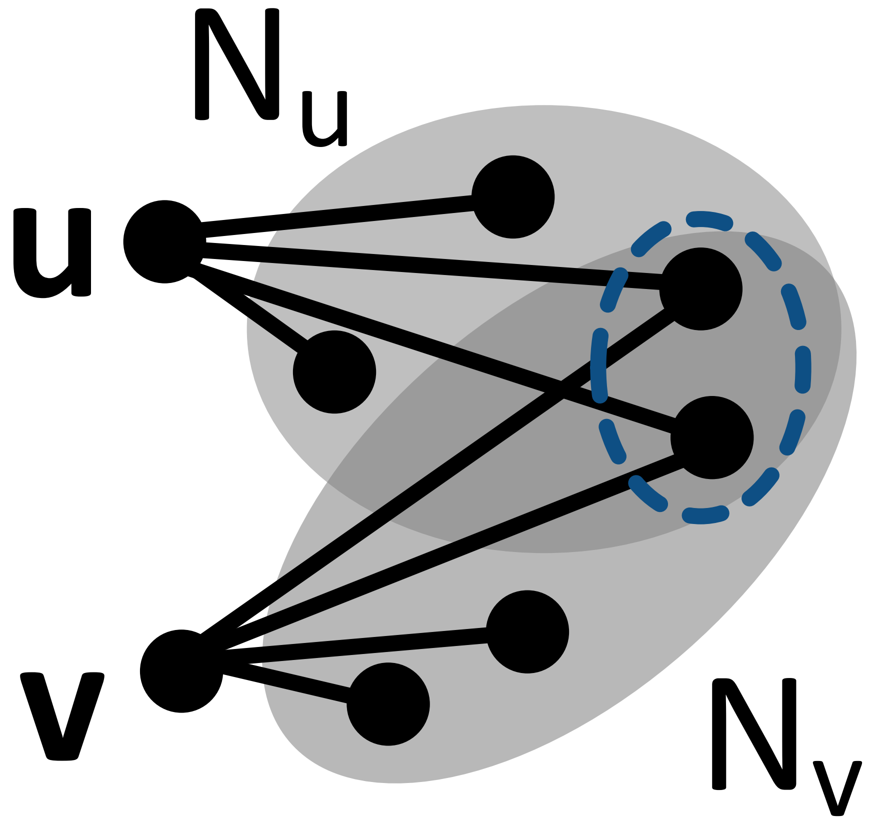

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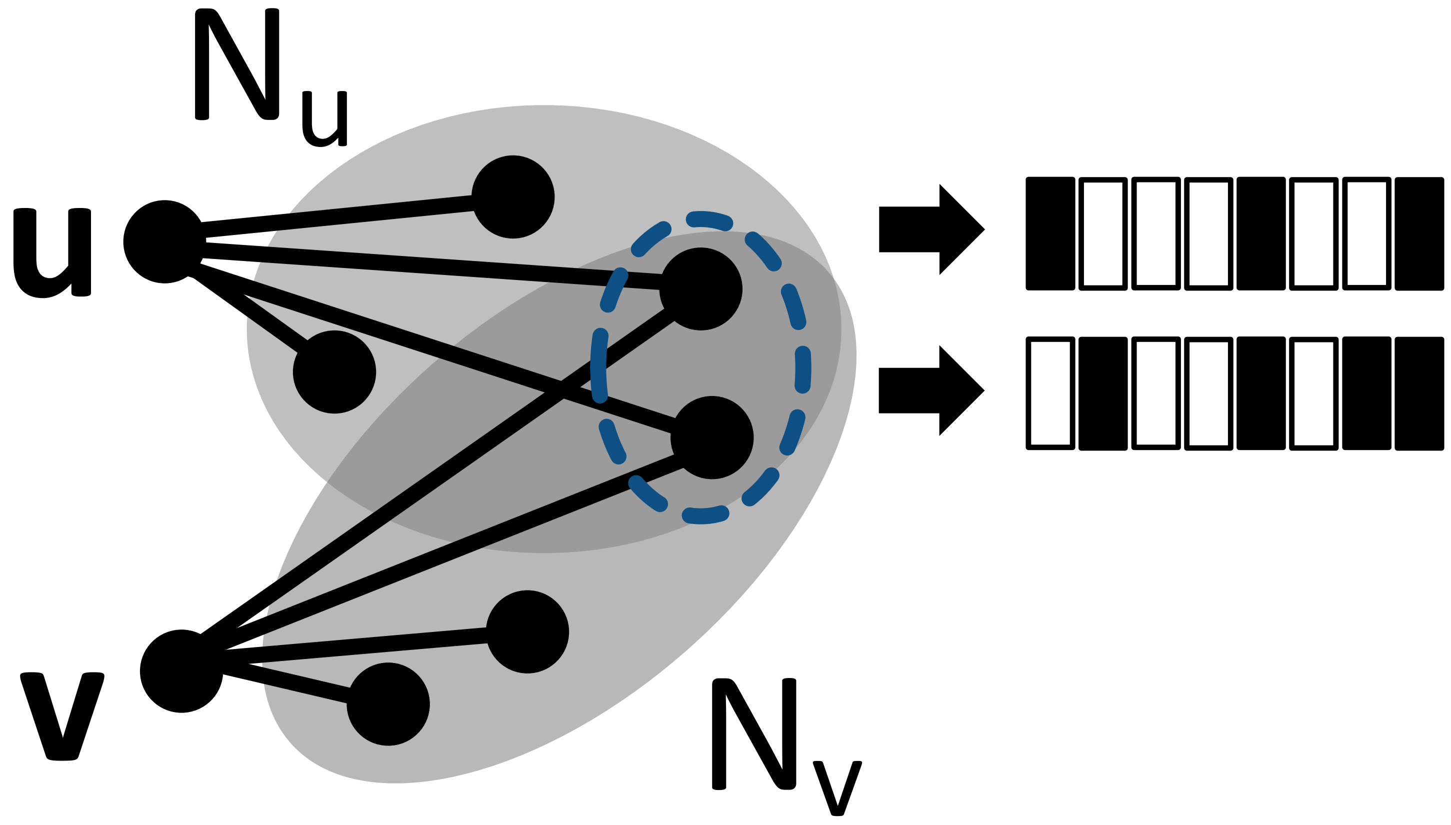

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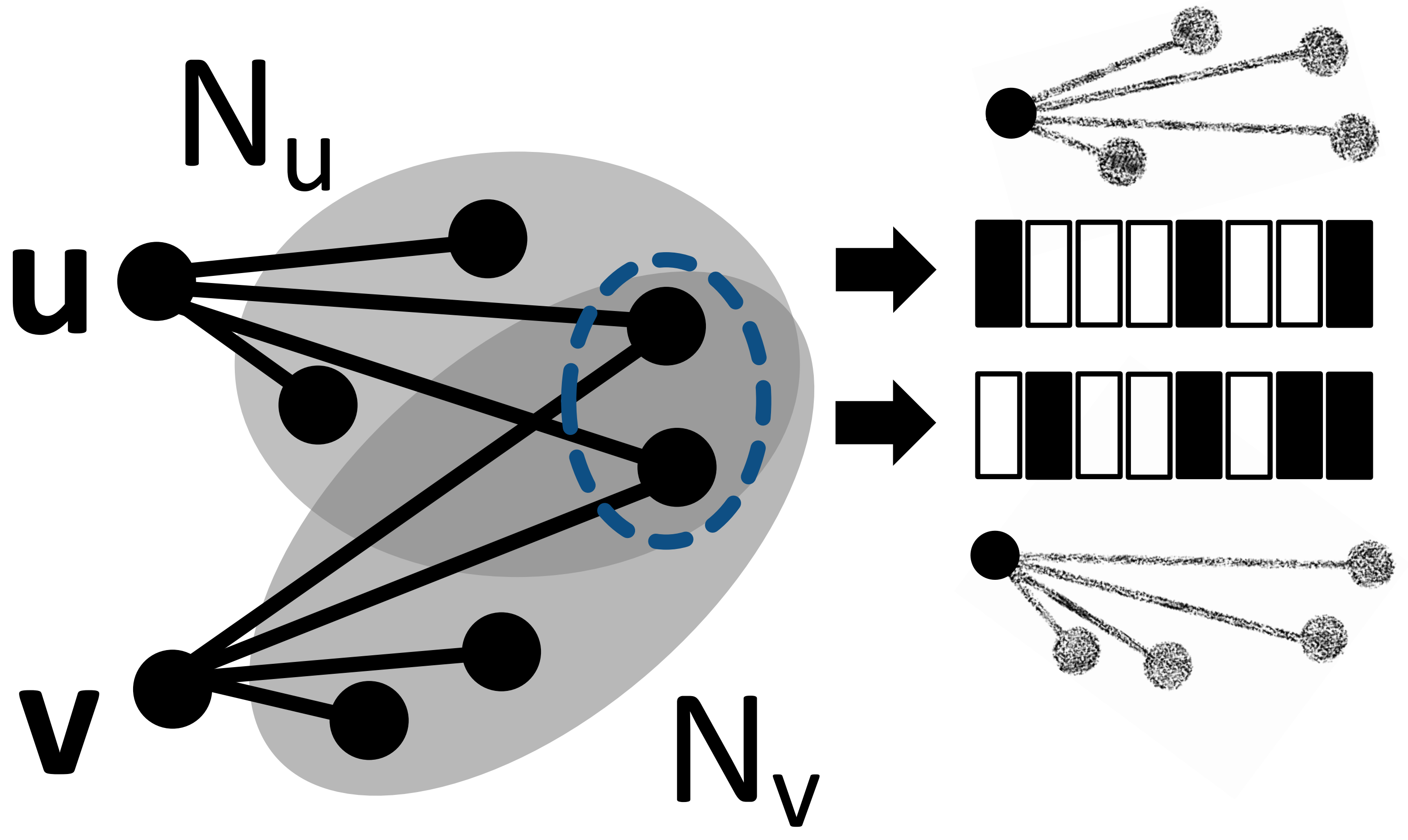

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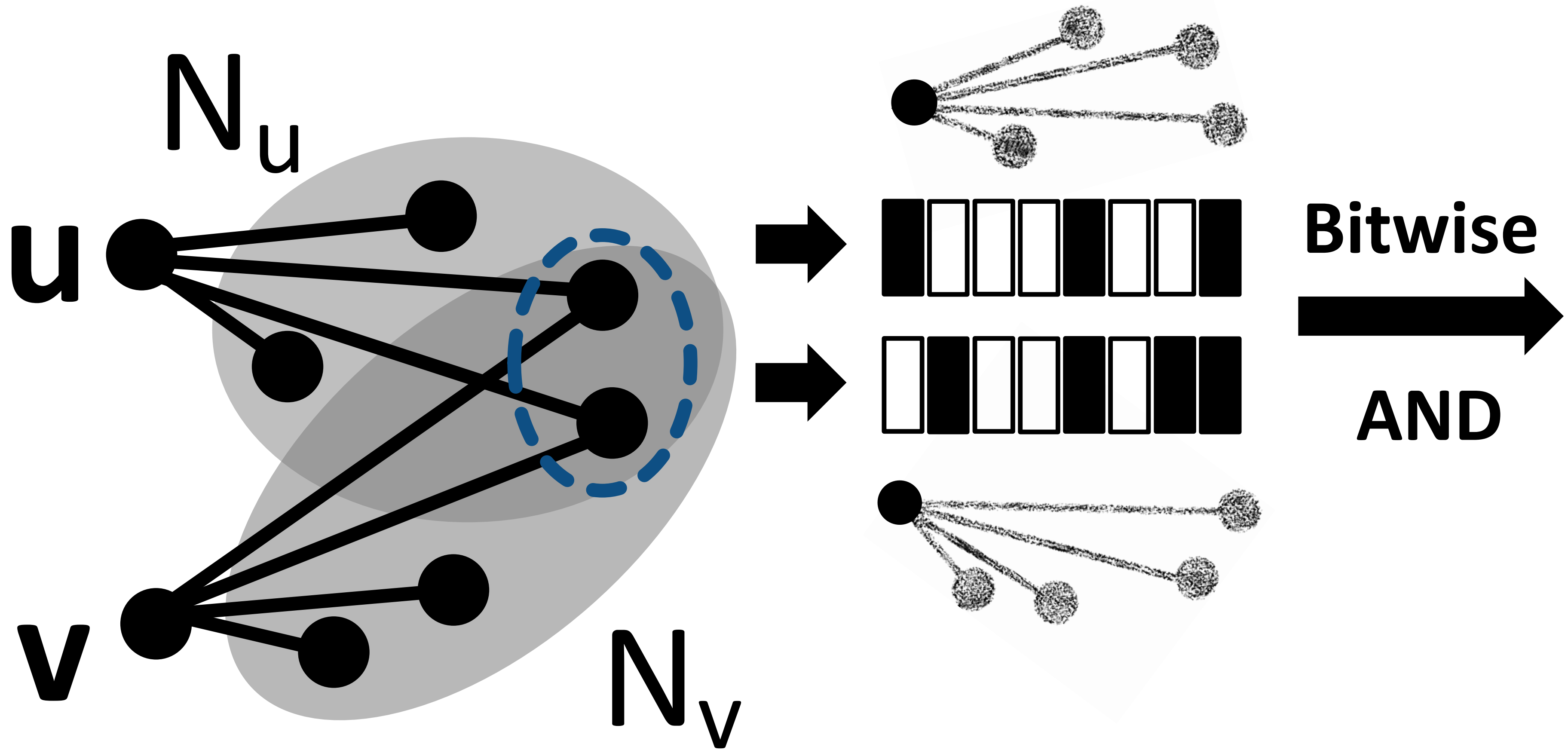

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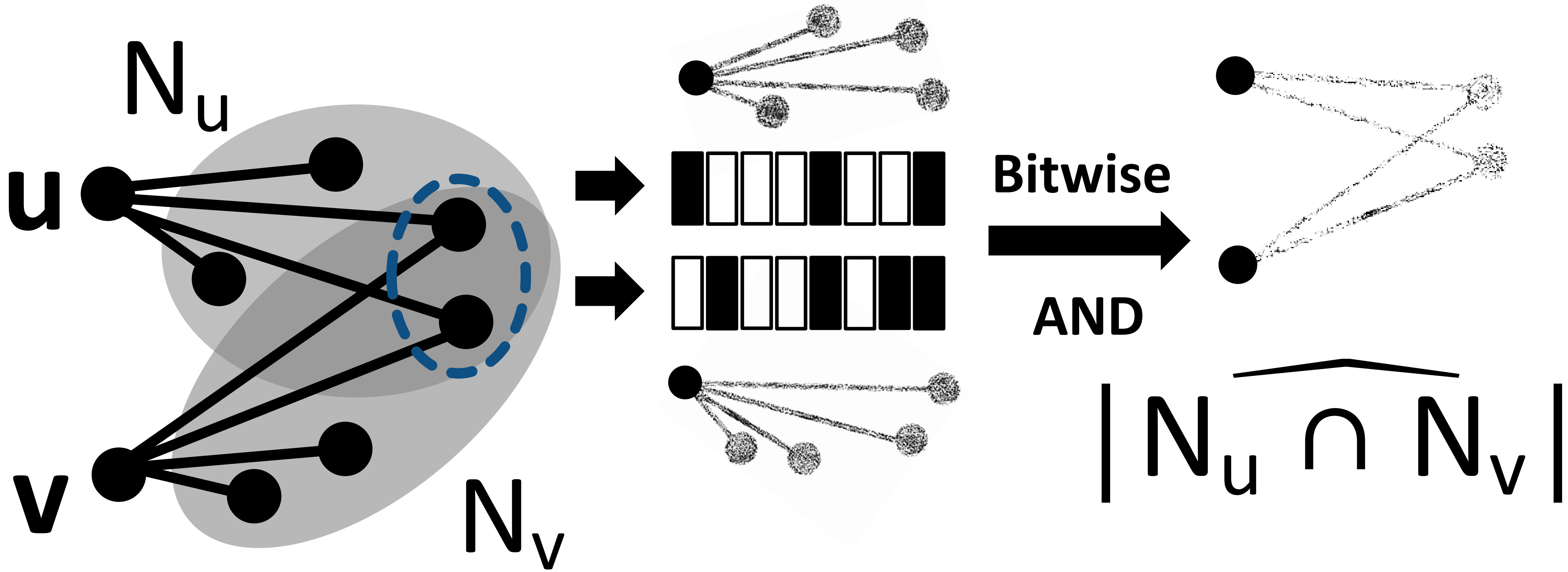

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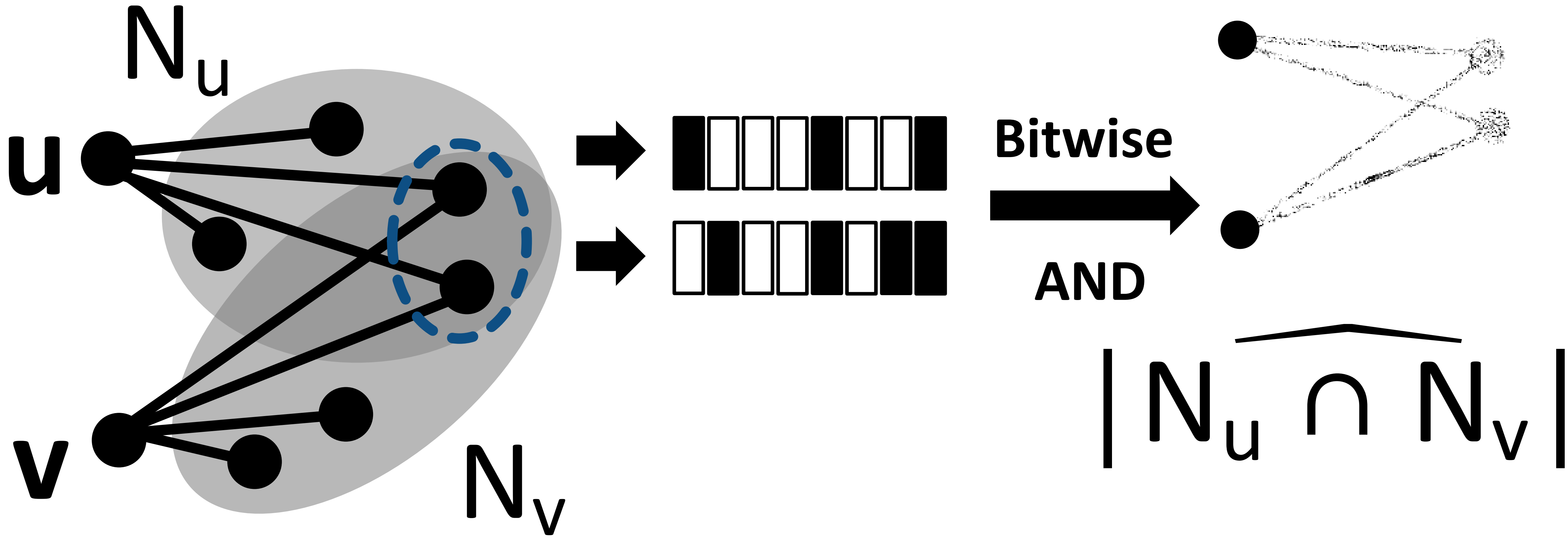

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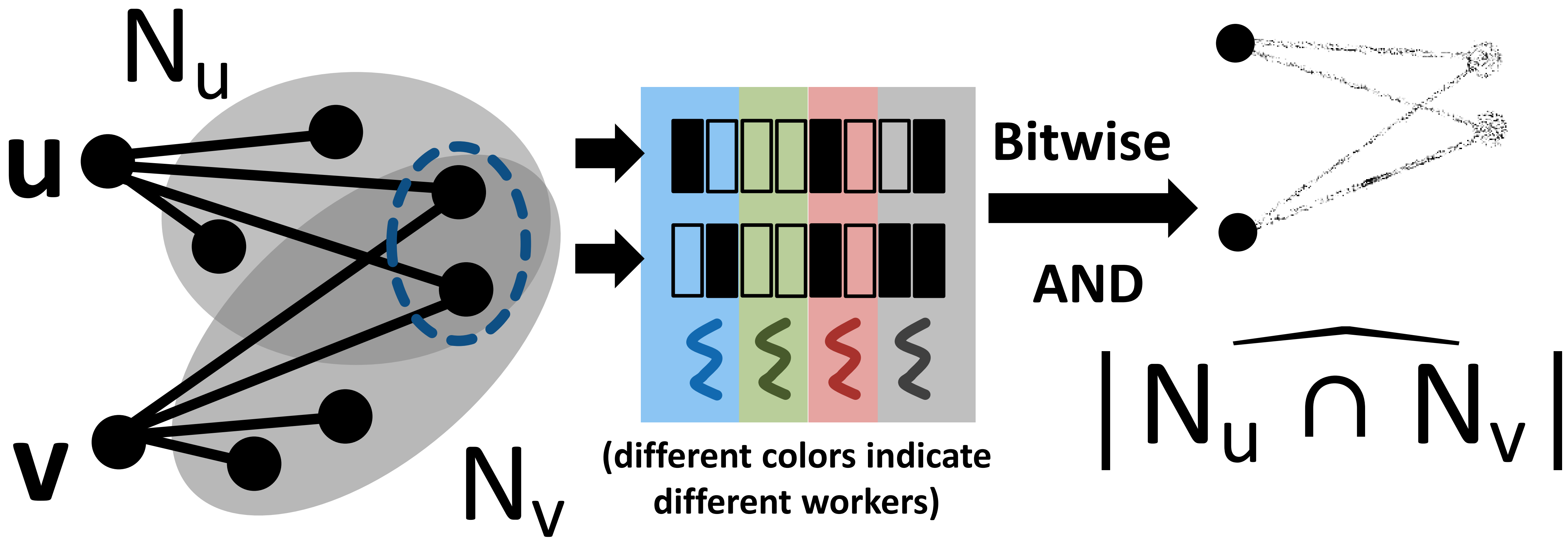

(different colors indicate different workers)

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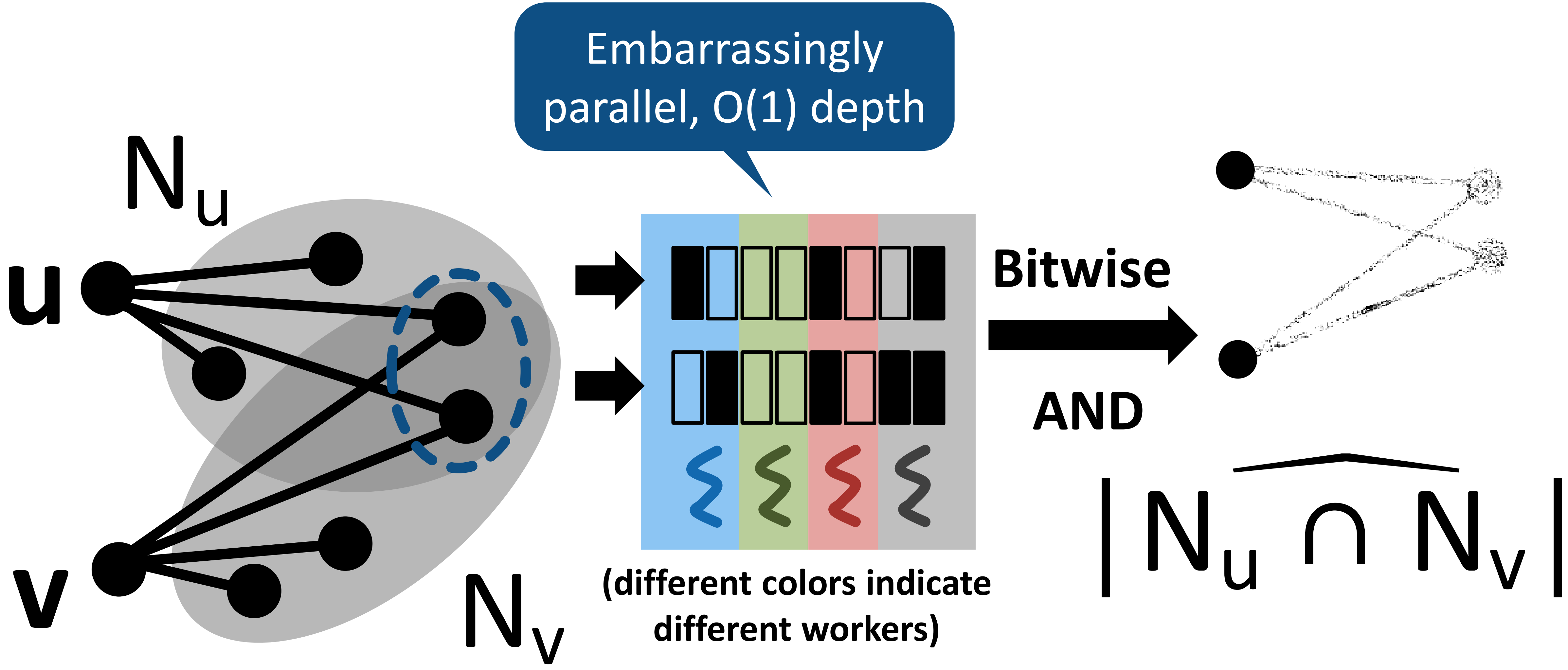

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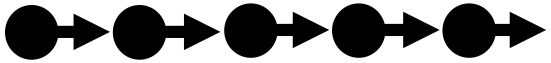

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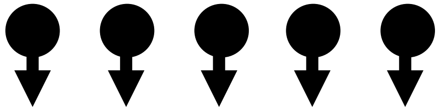

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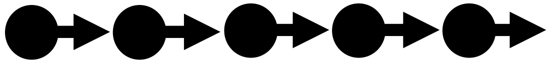

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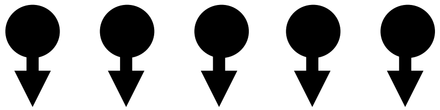

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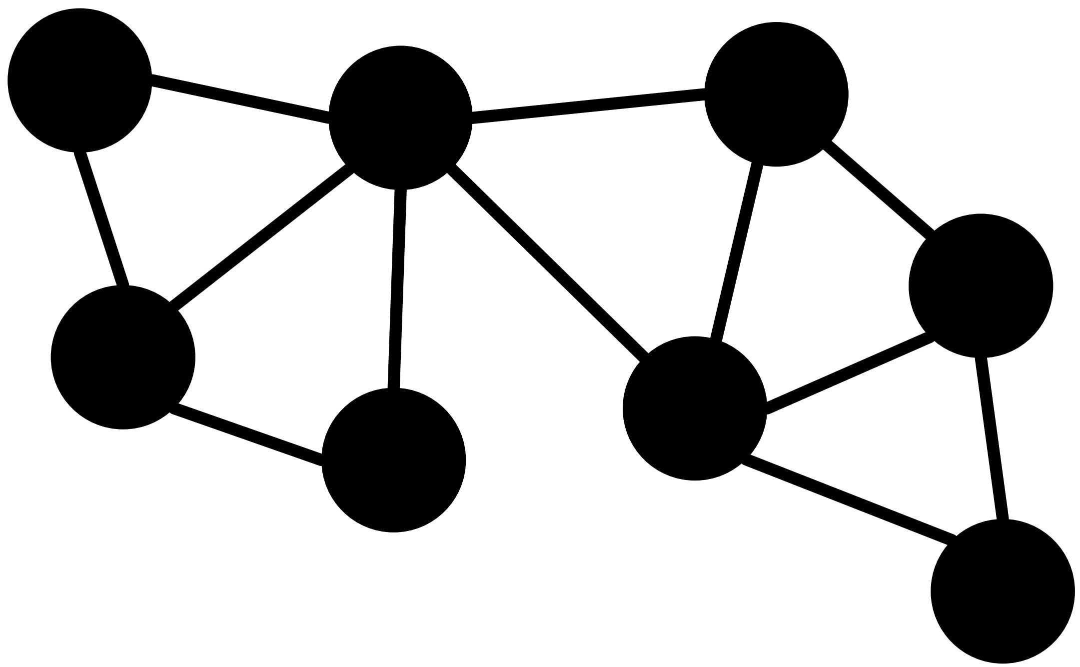
Let's see 4 example use cases...

Use Case 1: Link Prediction

Which links will appear?

Which links are missing?



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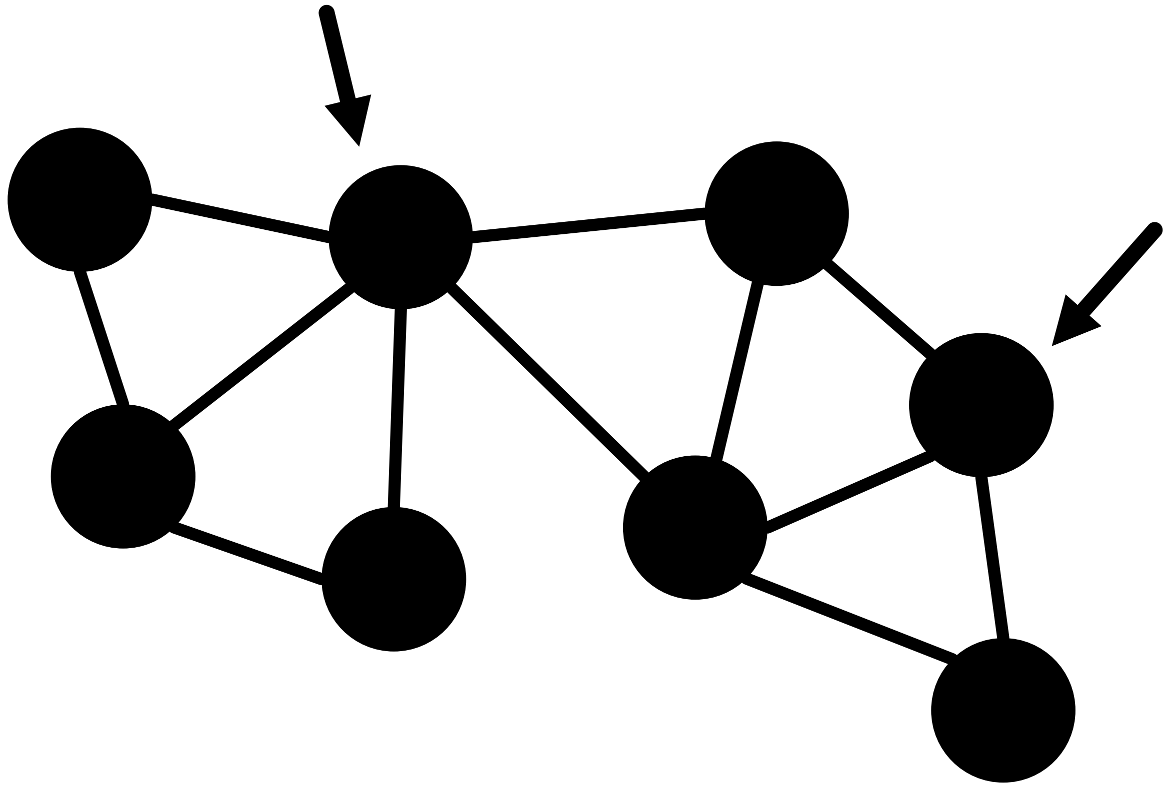

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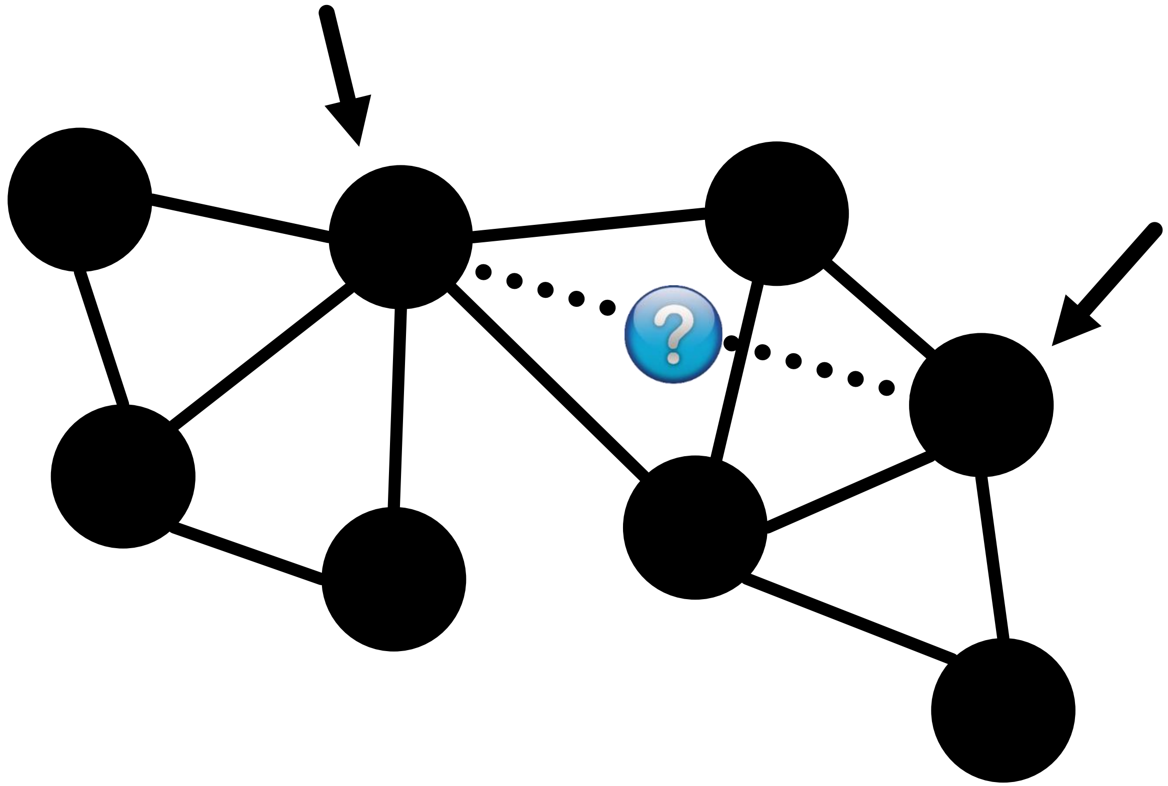

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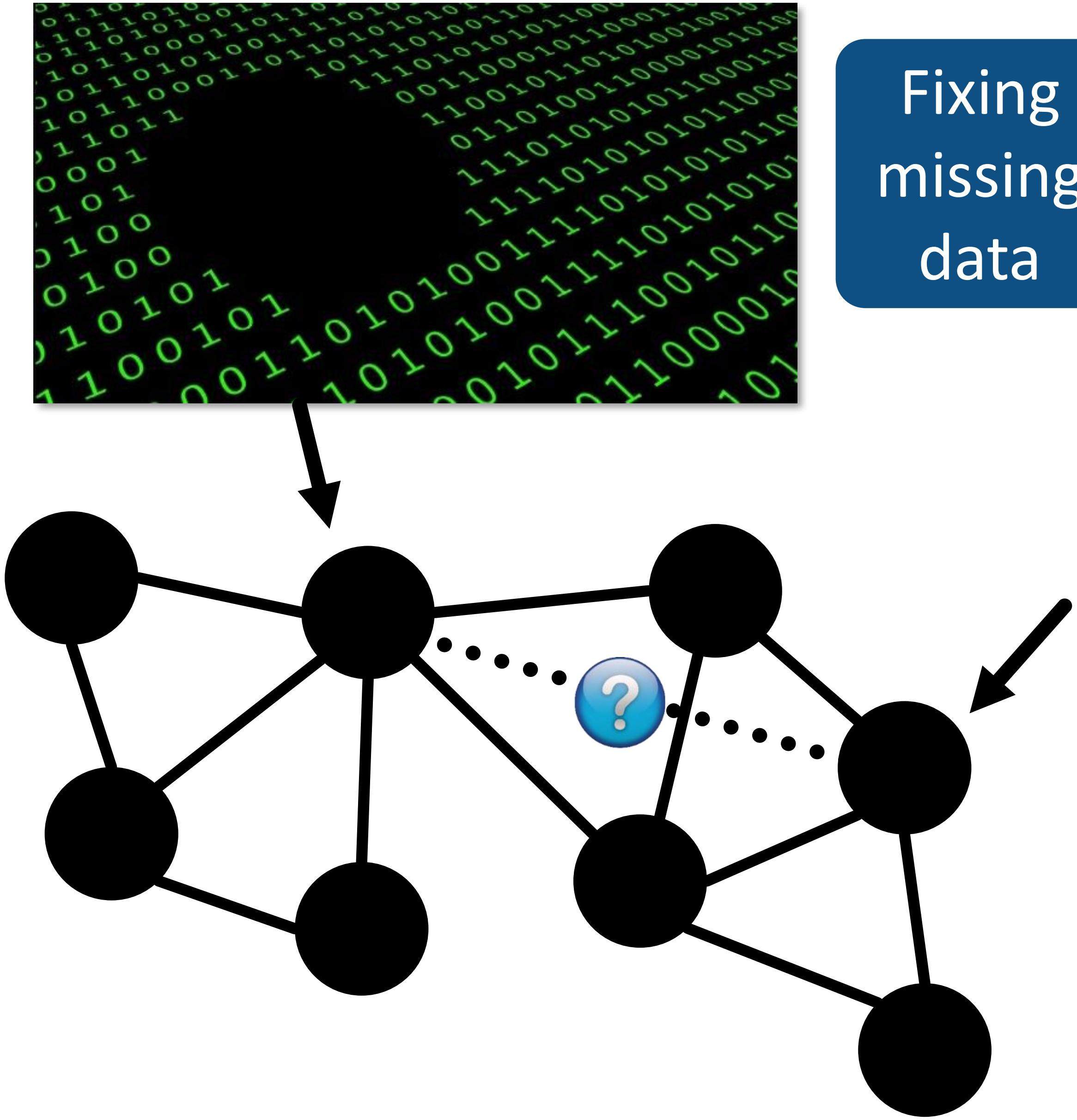

Fixing missing data

Predict future data

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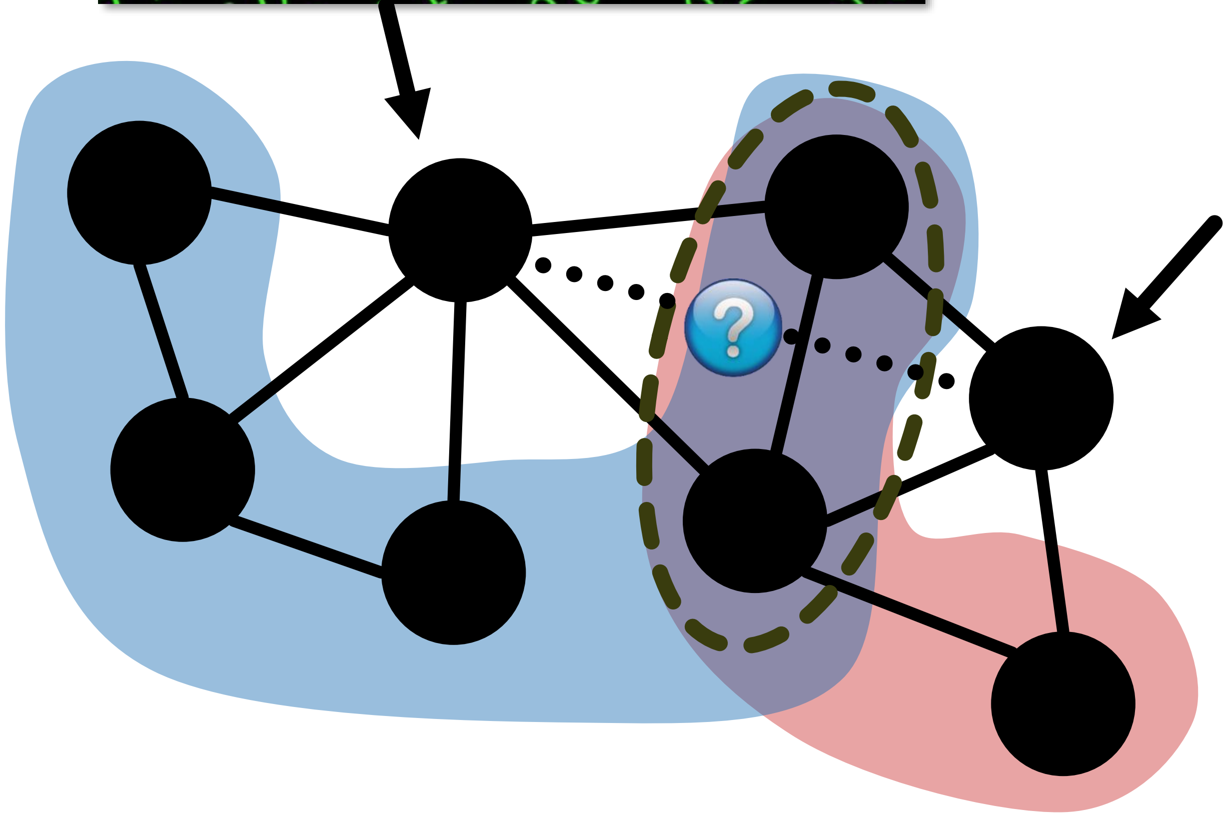

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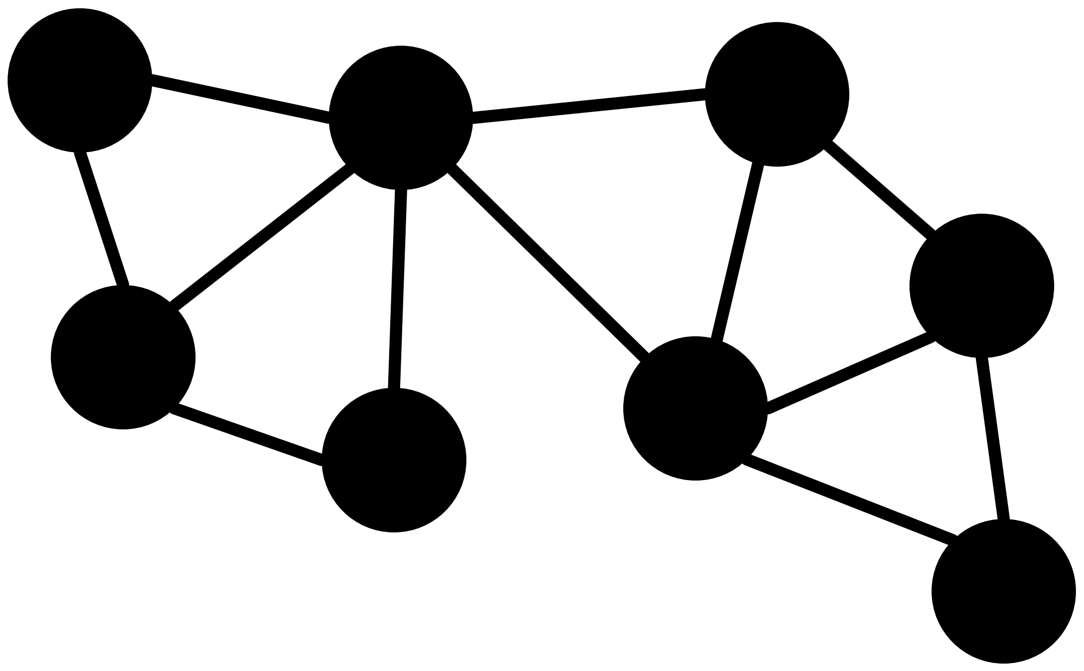

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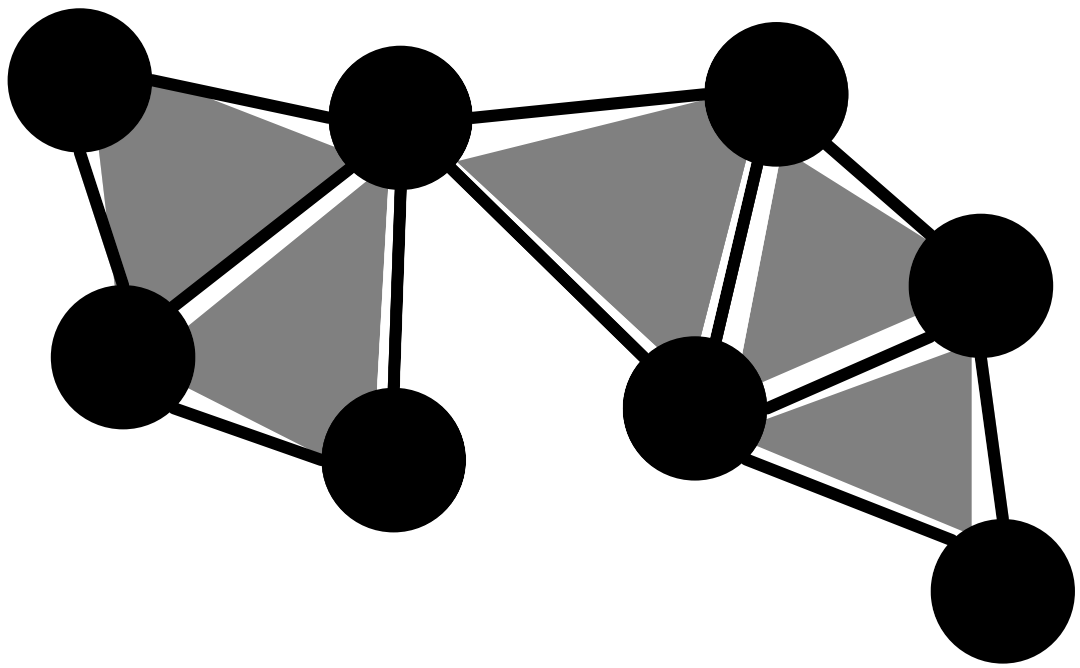

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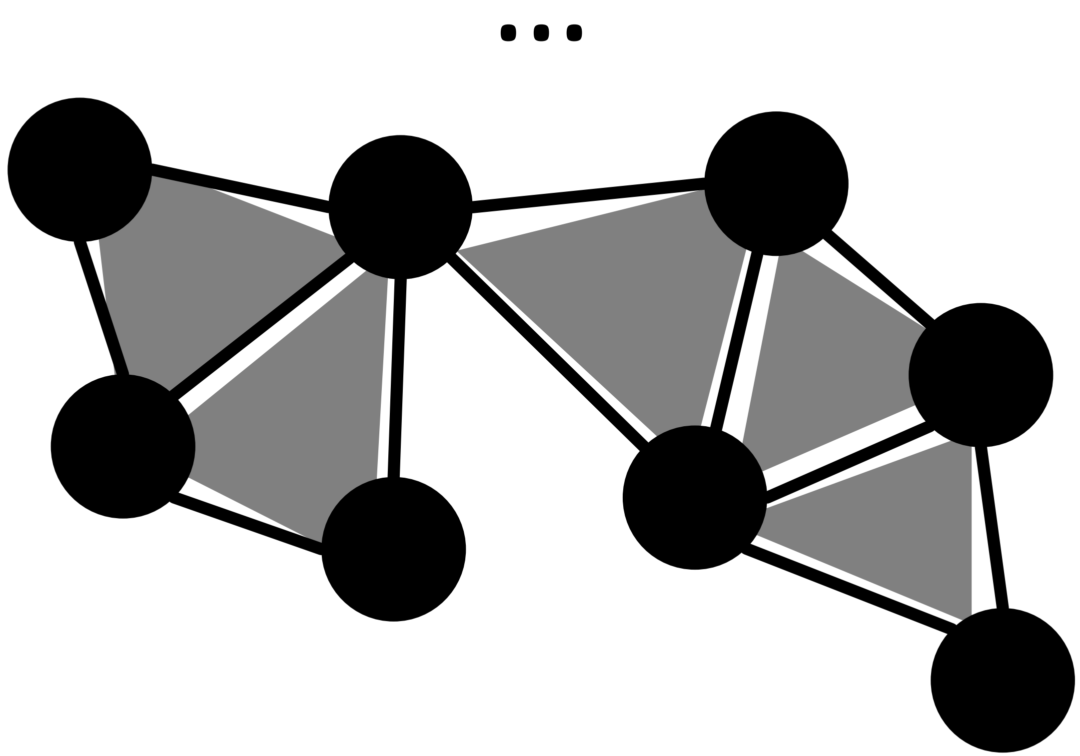

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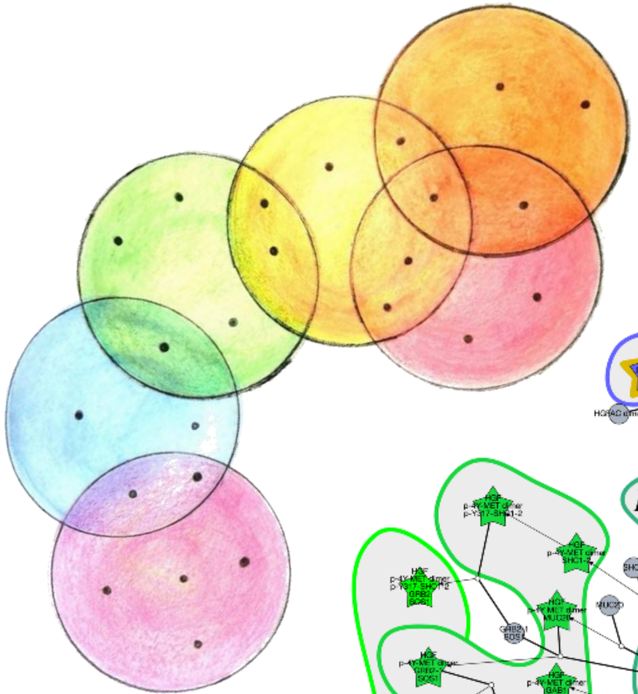
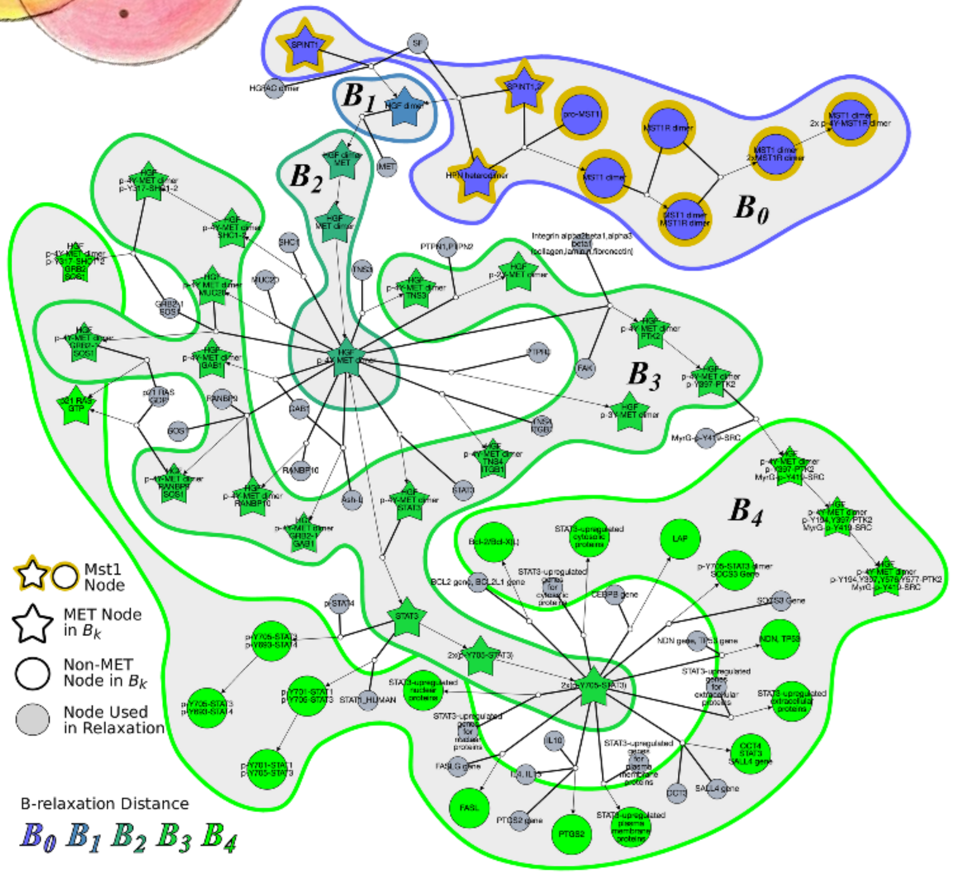
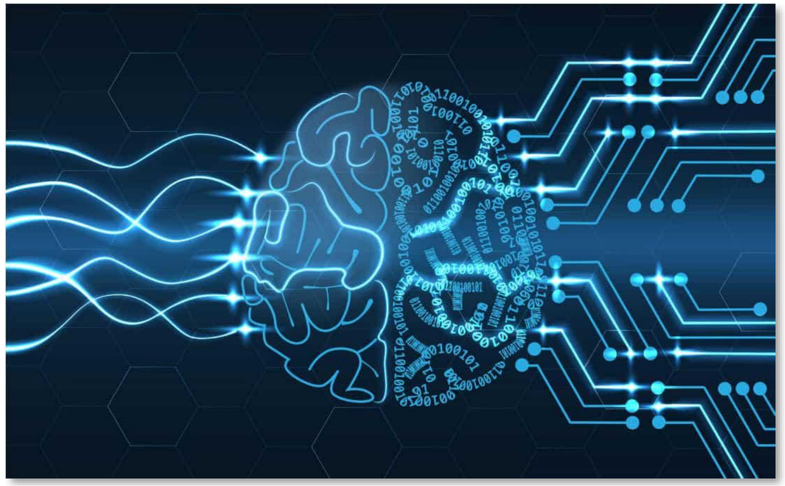




Learning over higher-order networks



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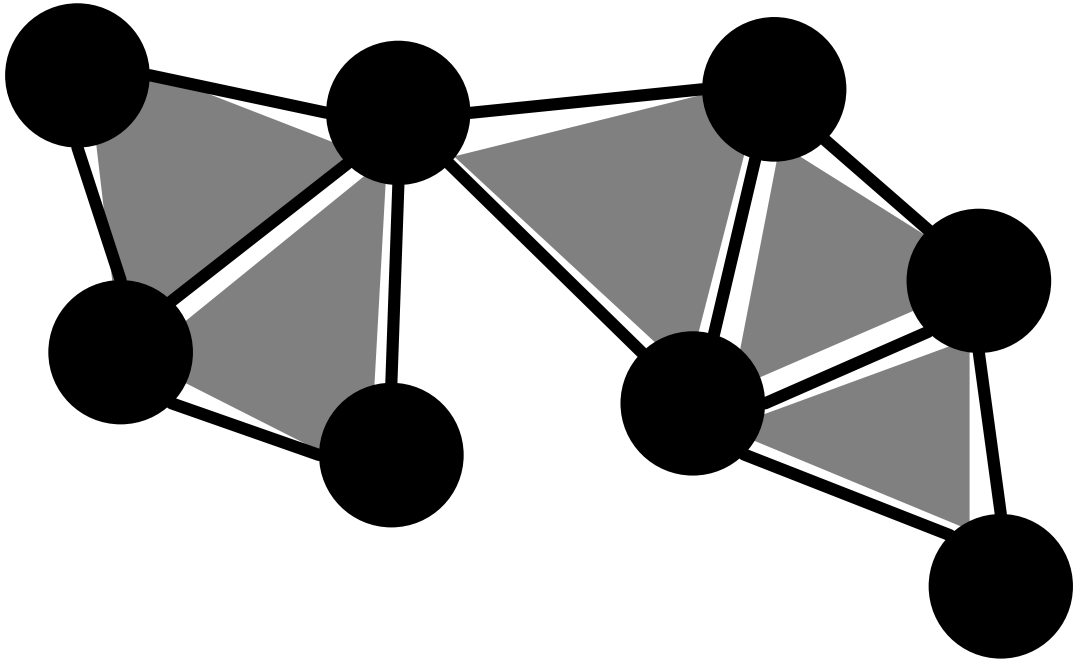
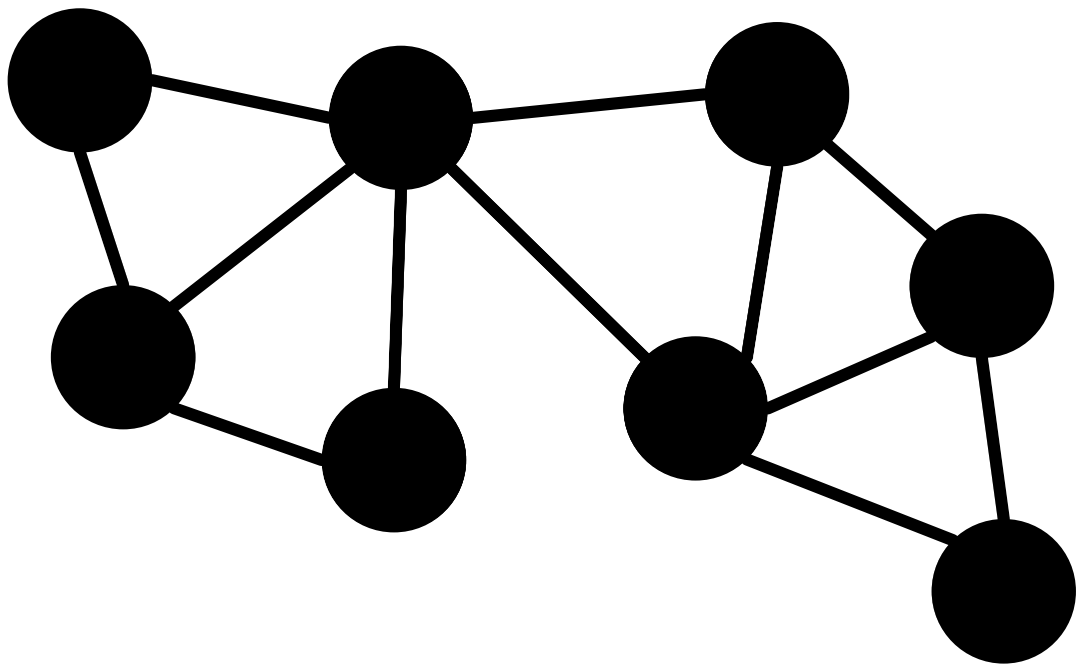


Use Case 3: Clustering

Clusters?

Structure of clusters?



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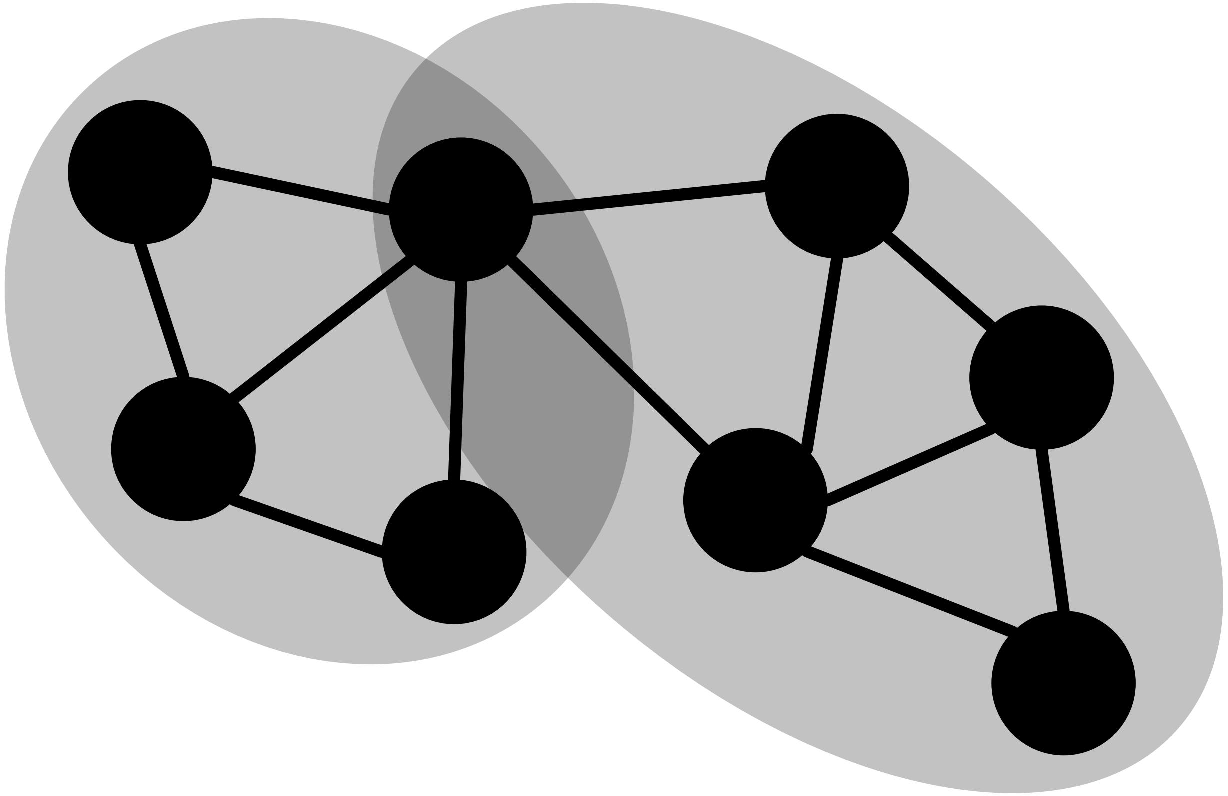

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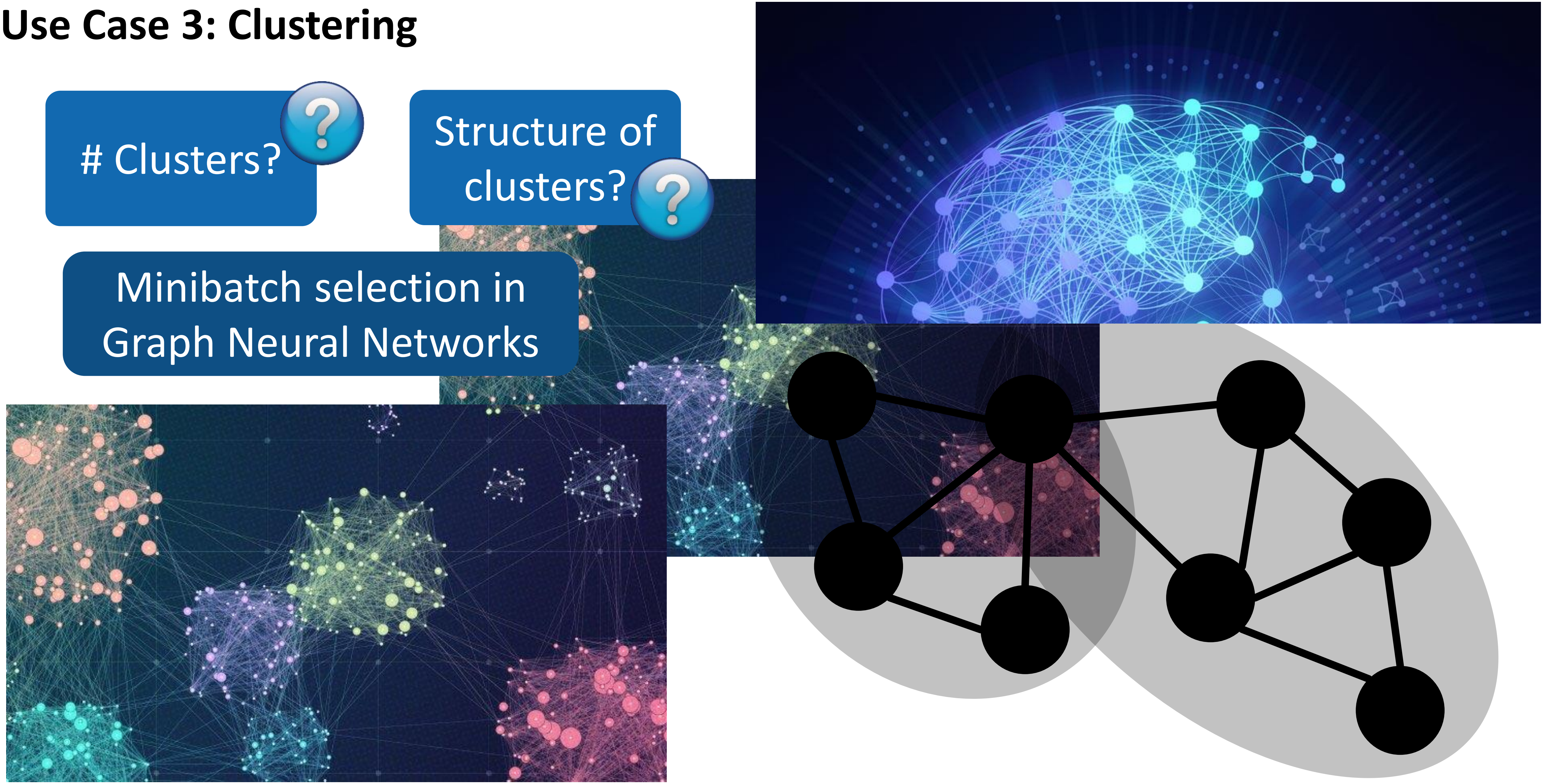
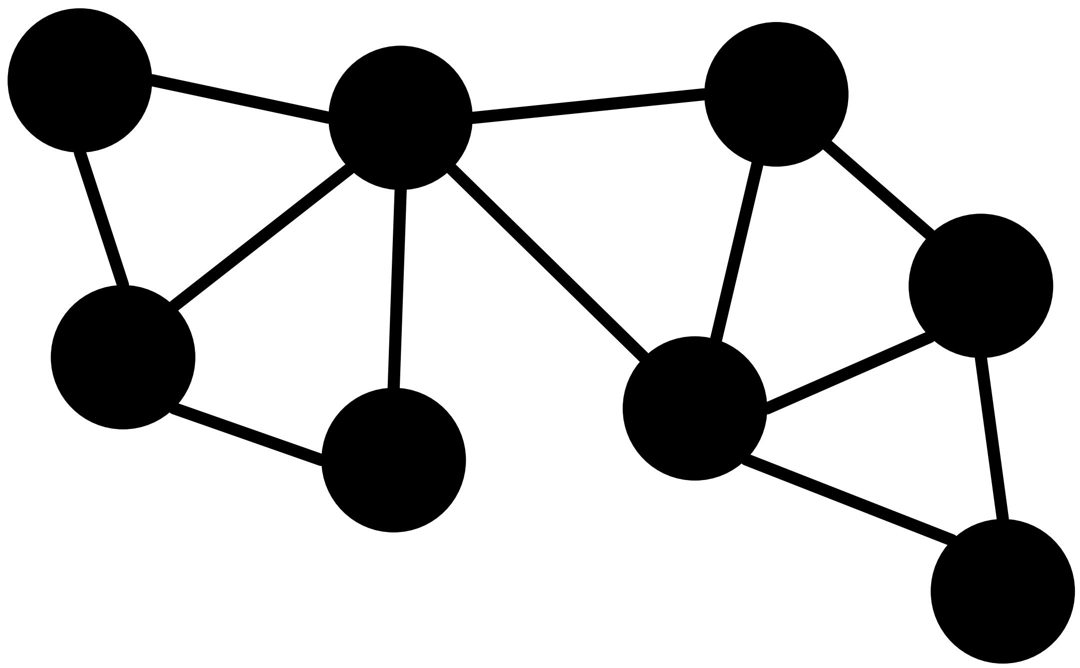
Minibatch selection in Graph Neural Networks



Use Case 4: Vertex Similarity



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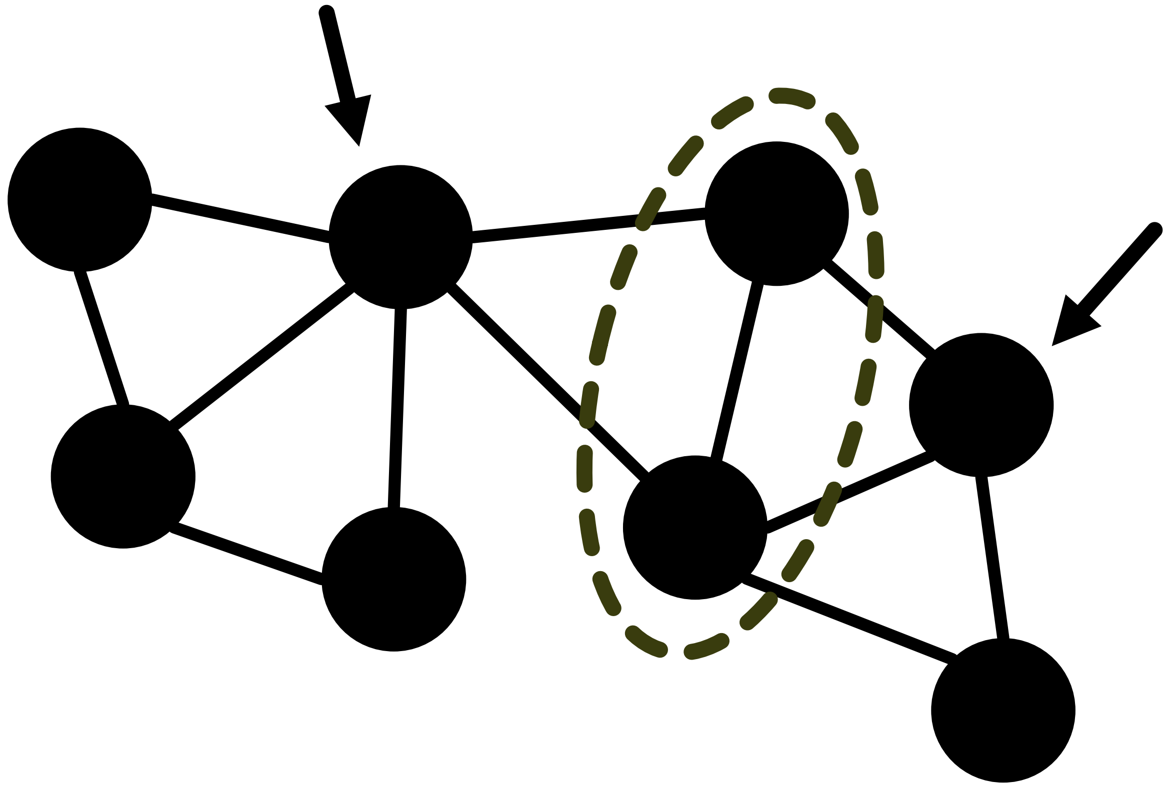

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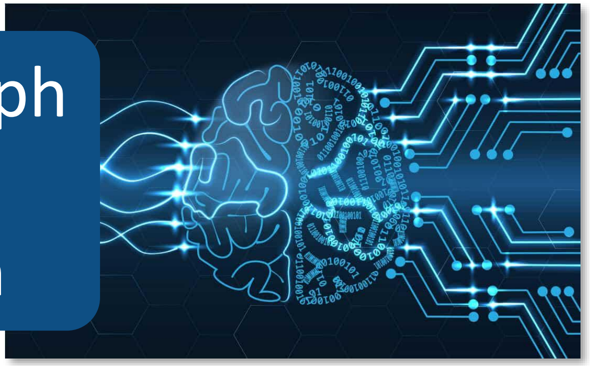
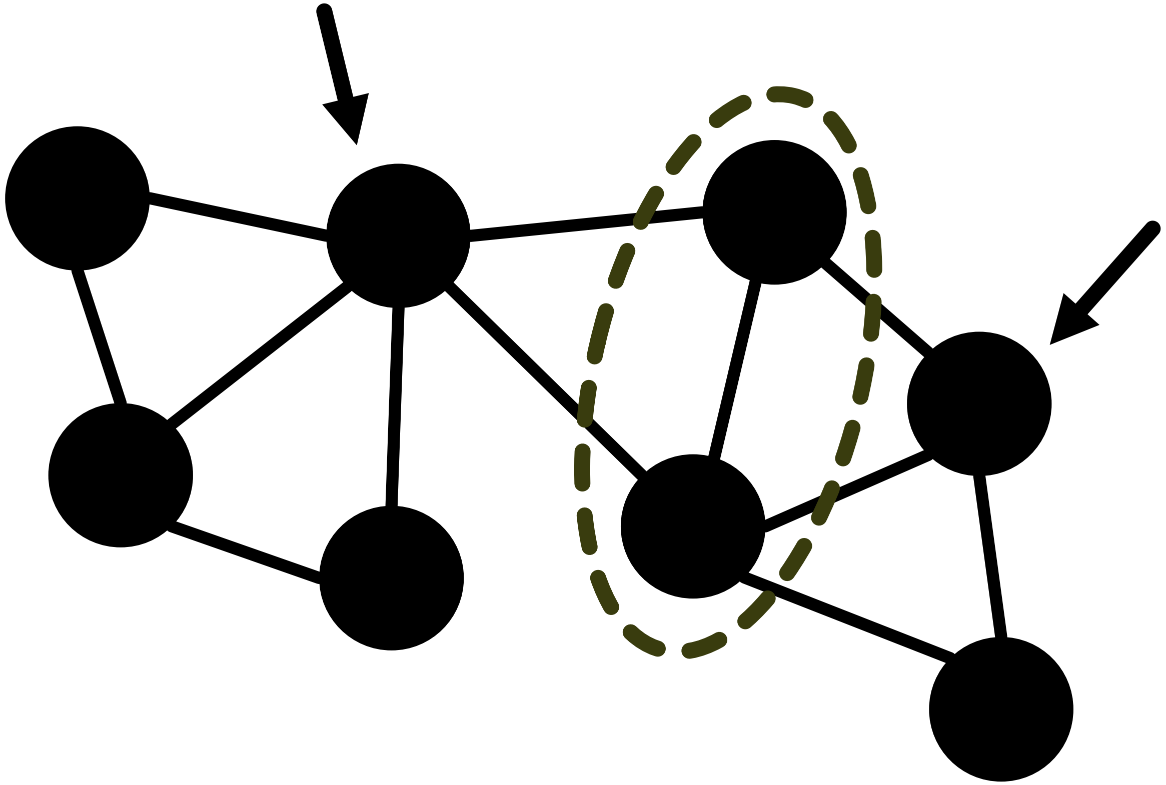
Enhancing graph embedding construction





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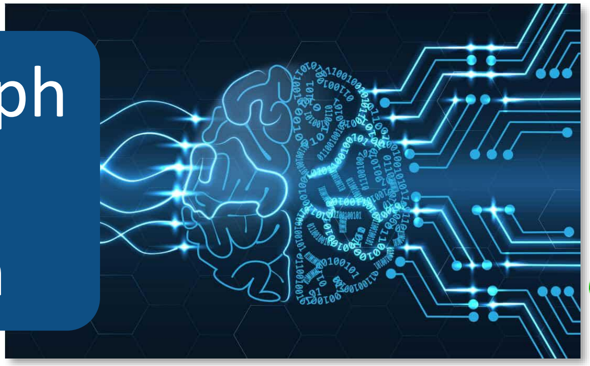

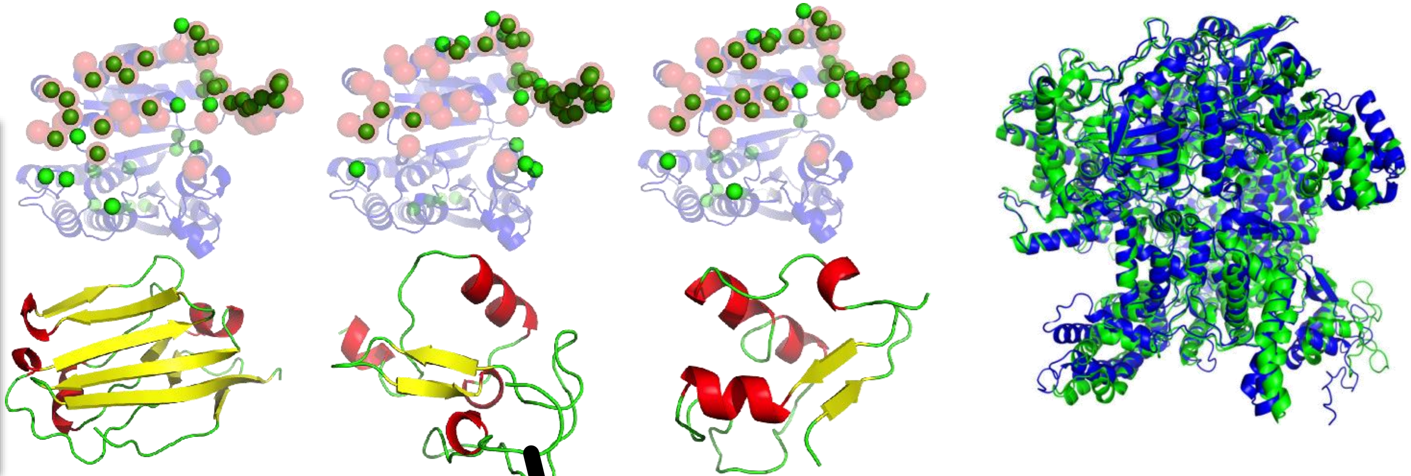

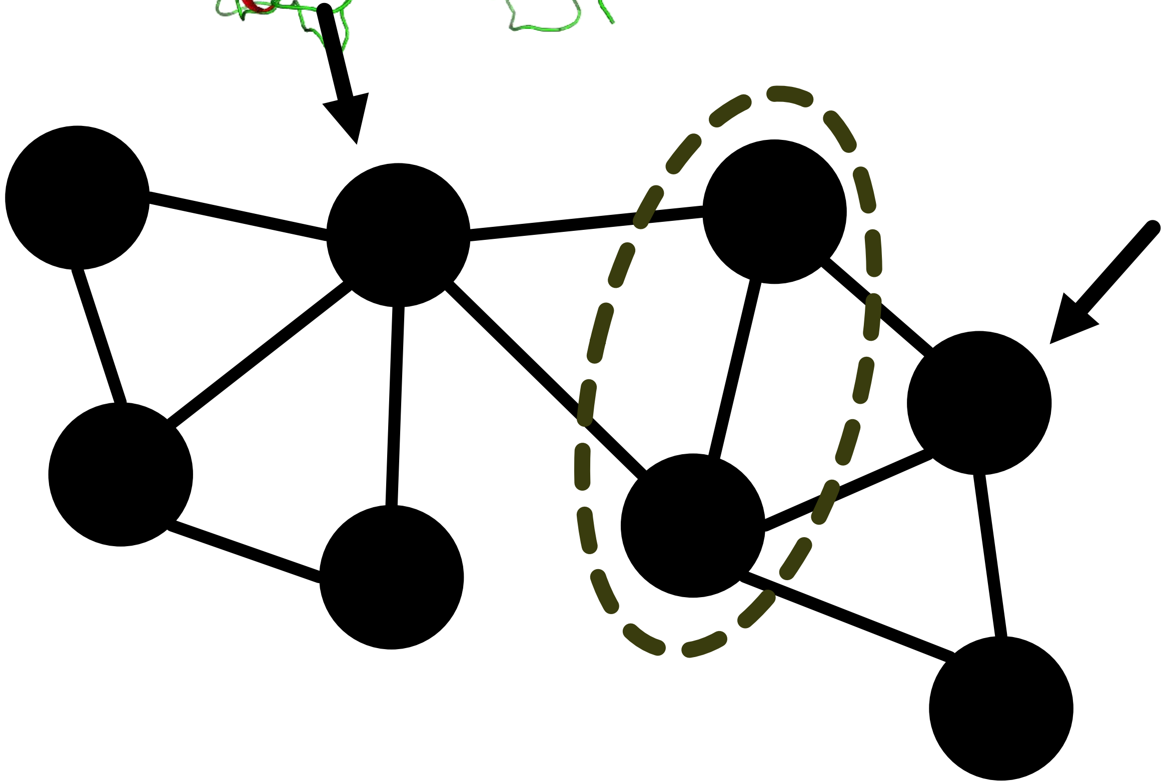

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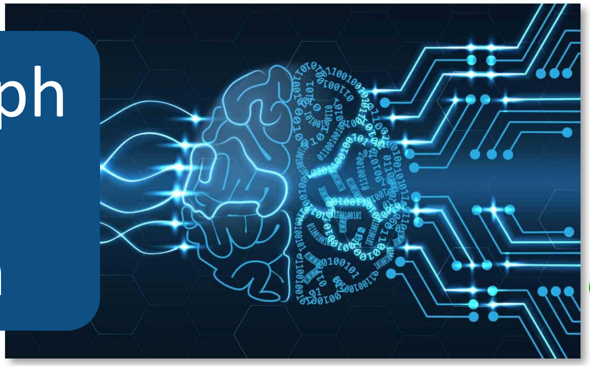

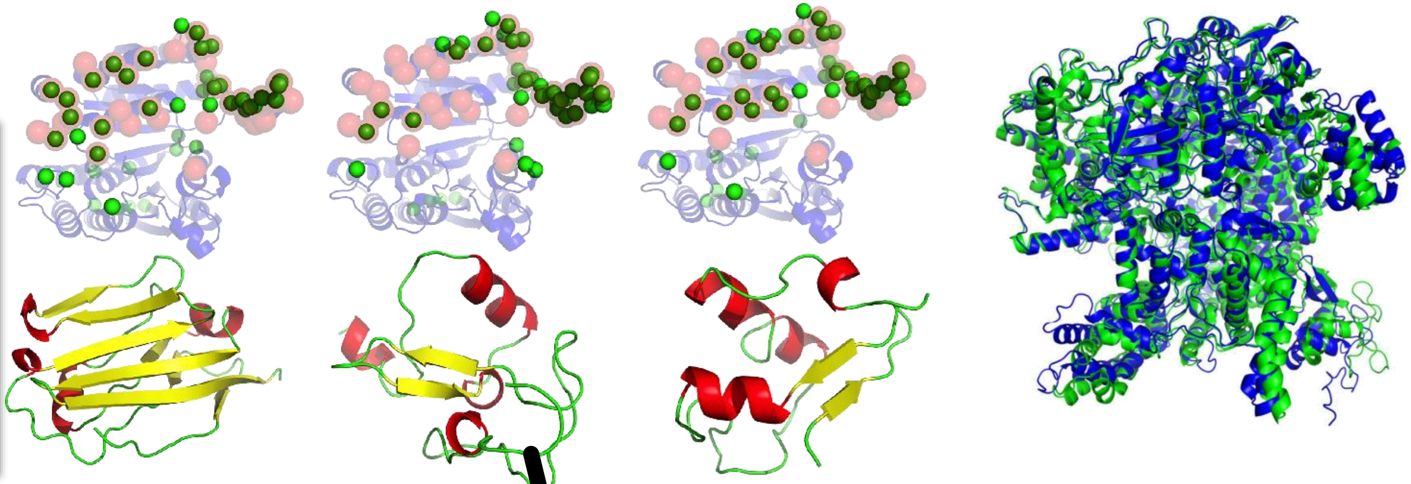

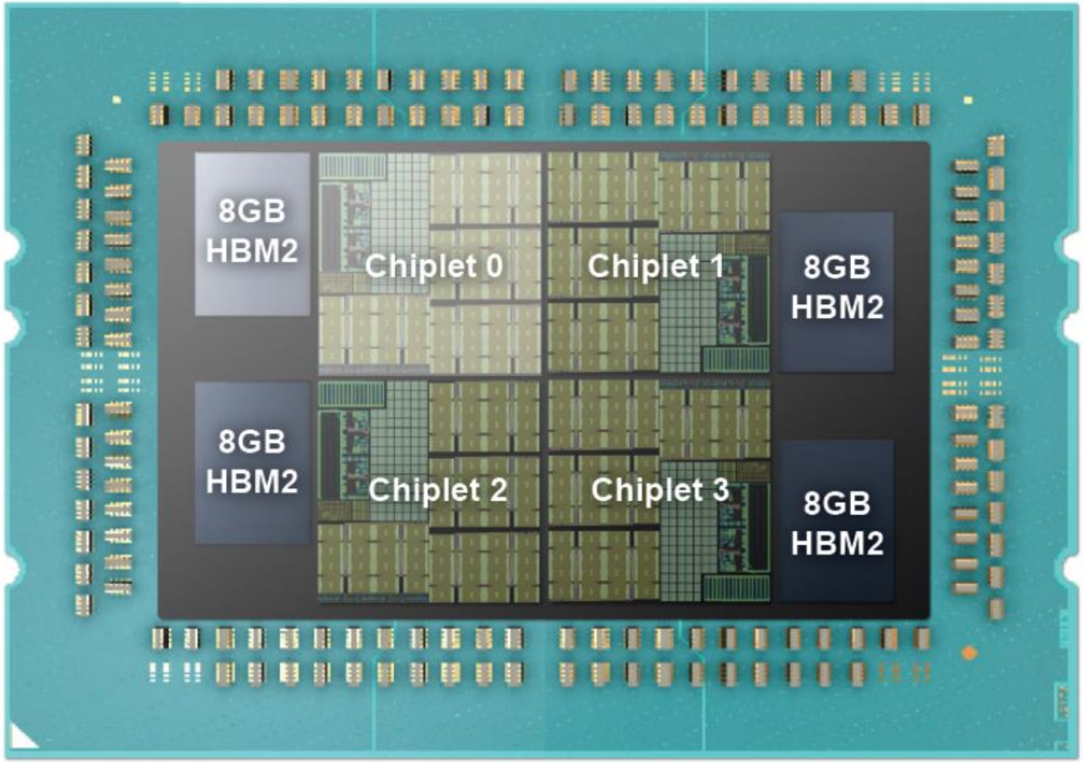

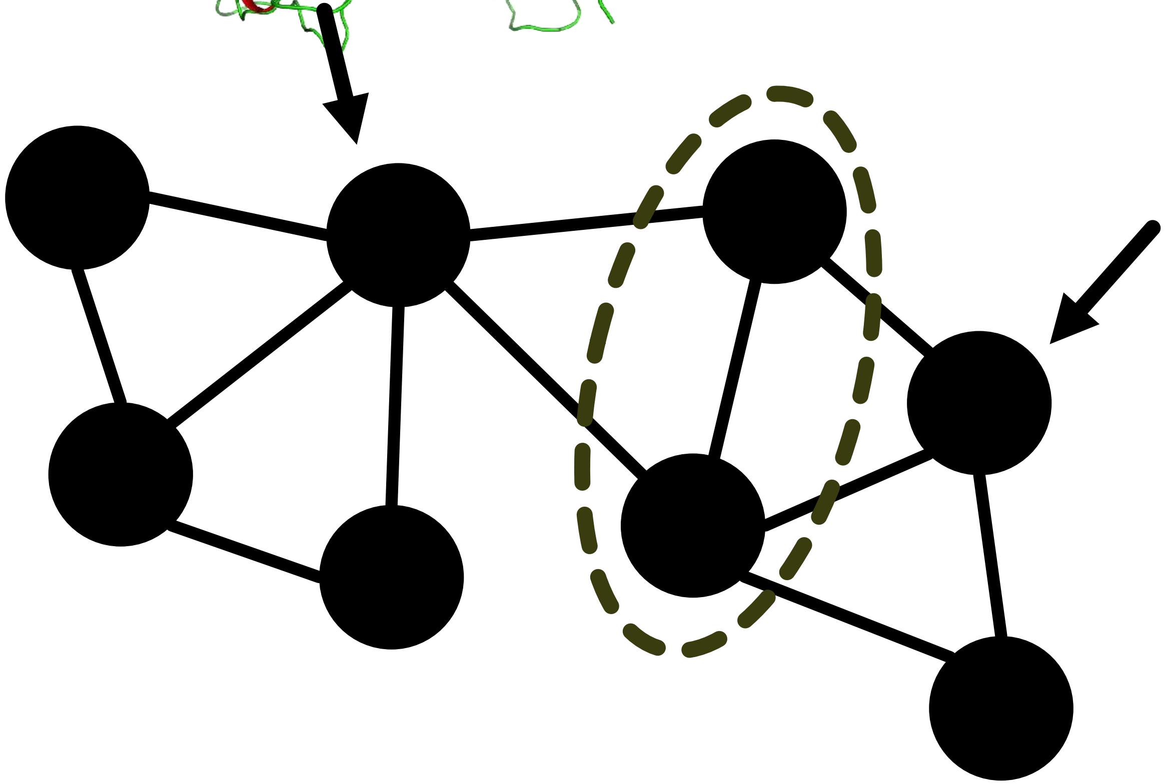

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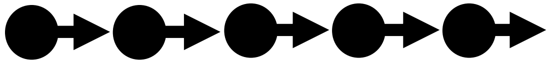

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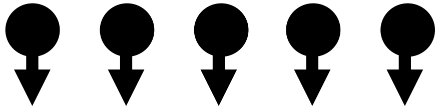

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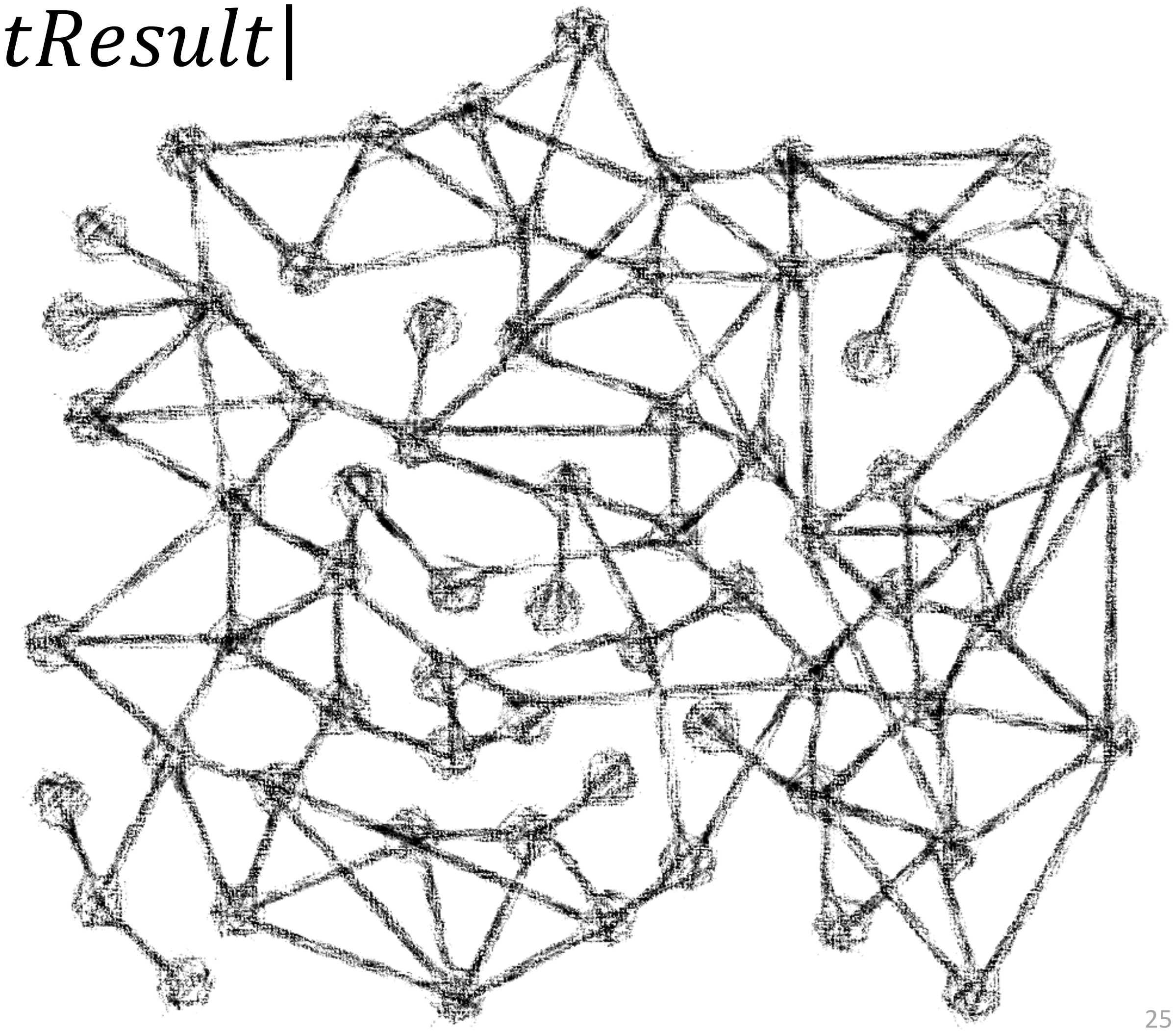

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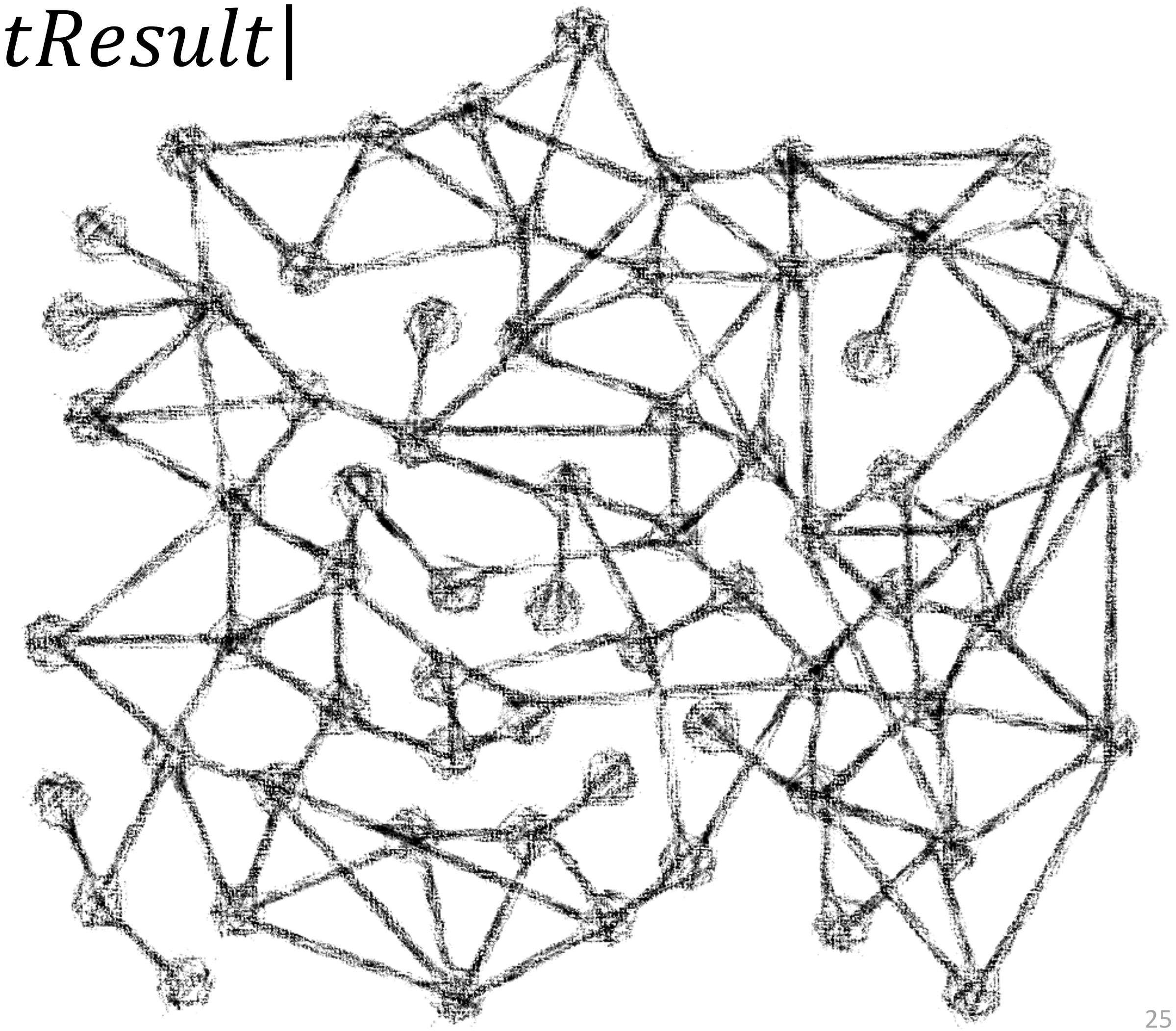
We incorporate statistical theory of estimators



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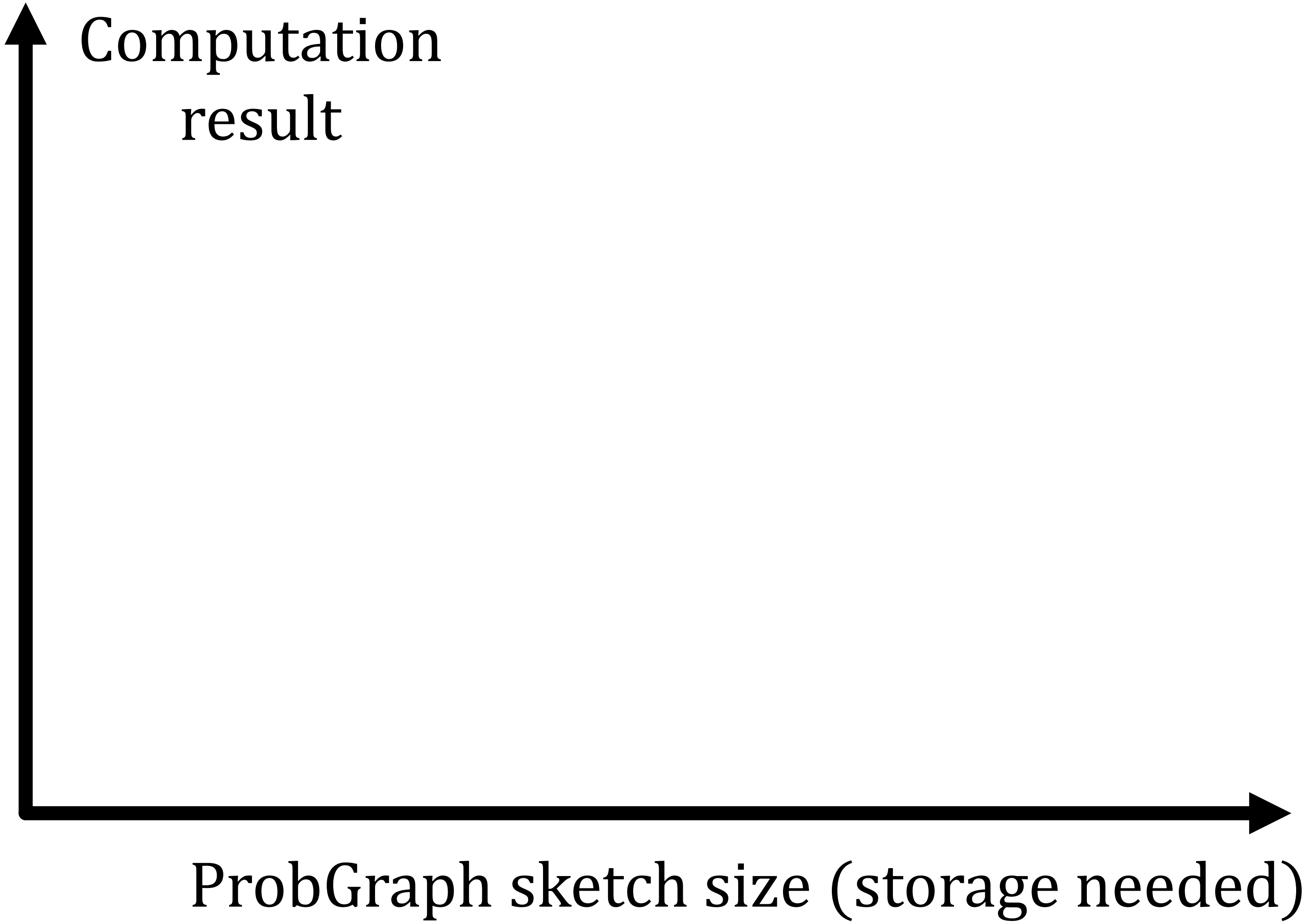

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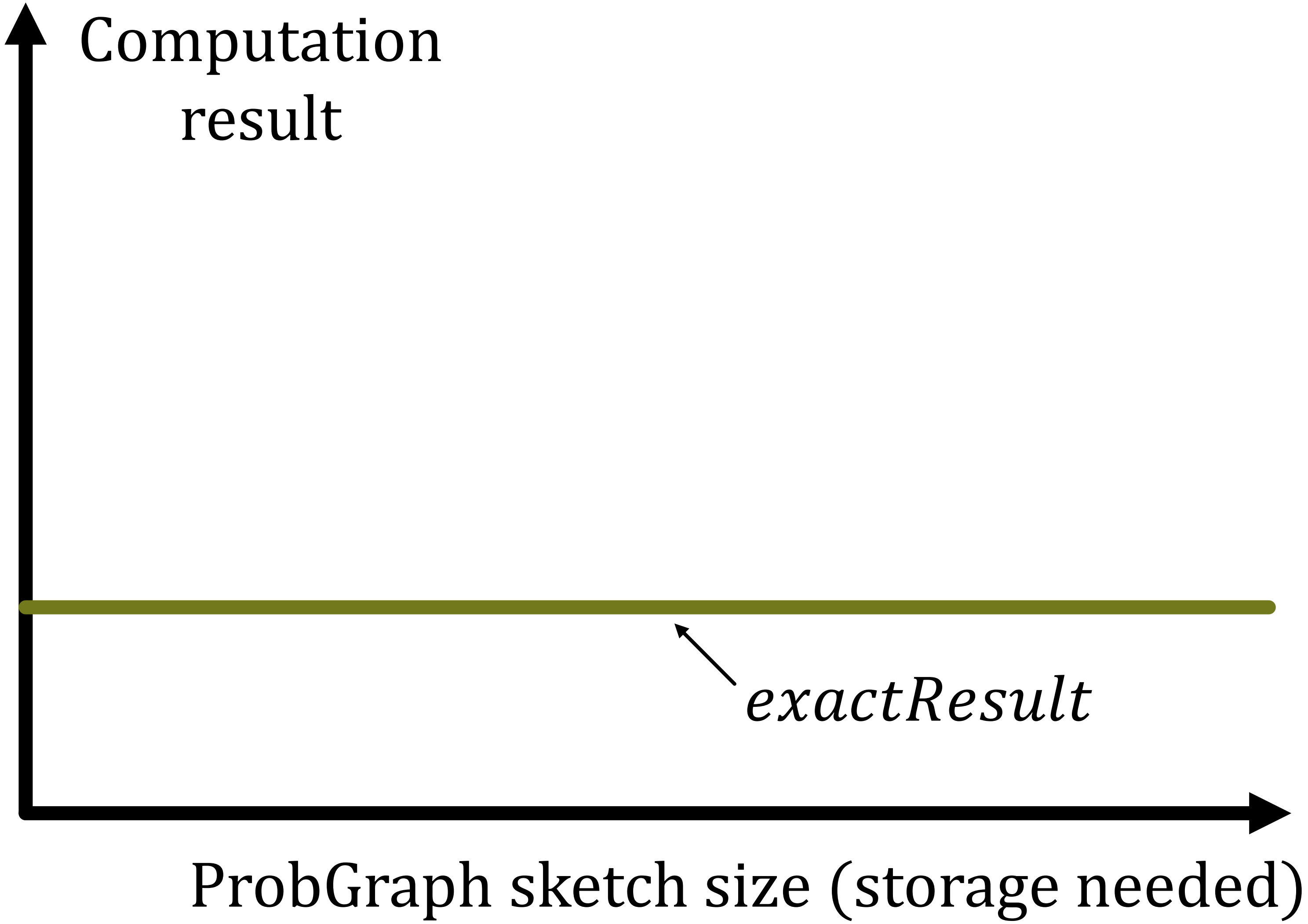

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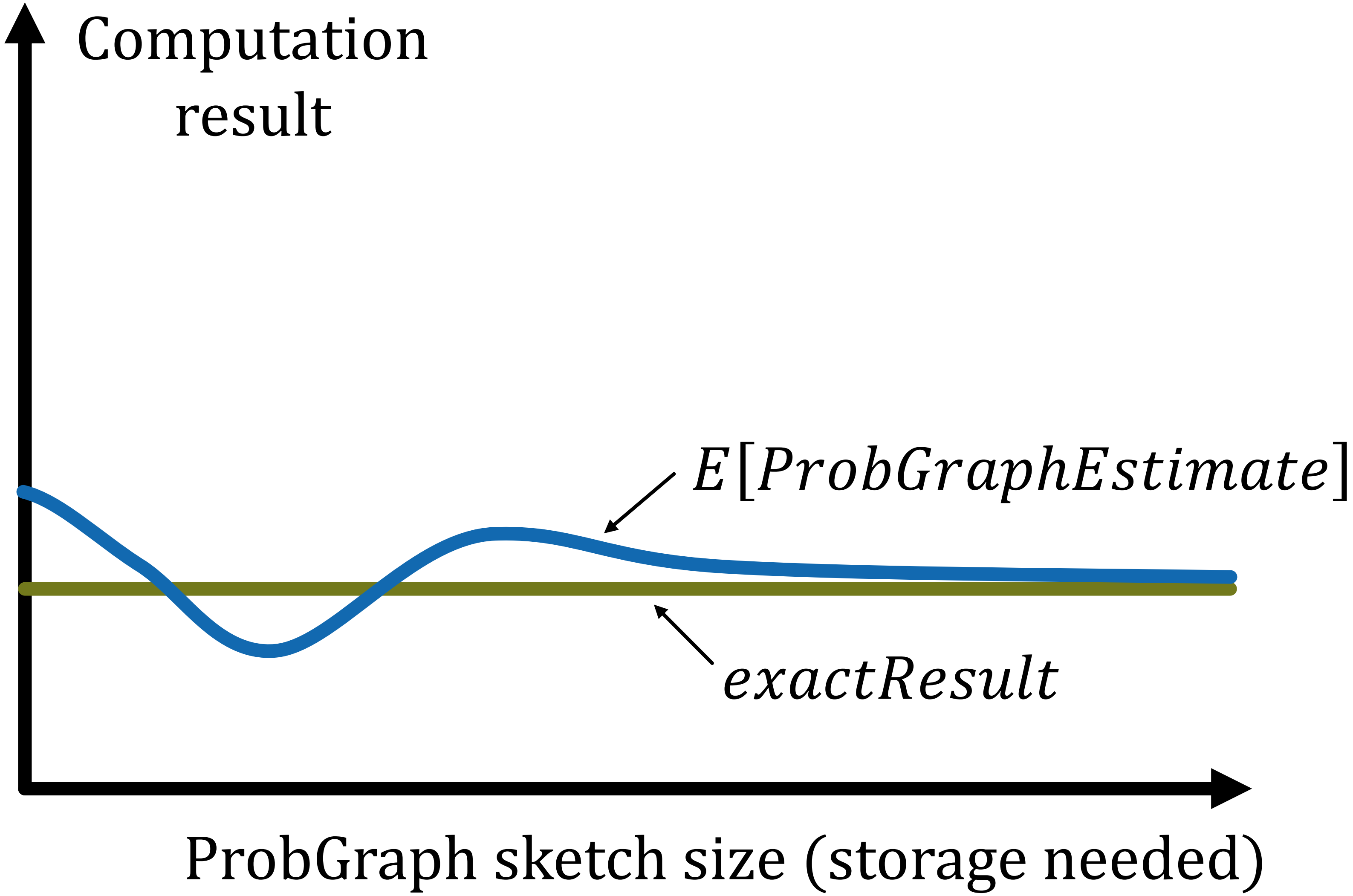

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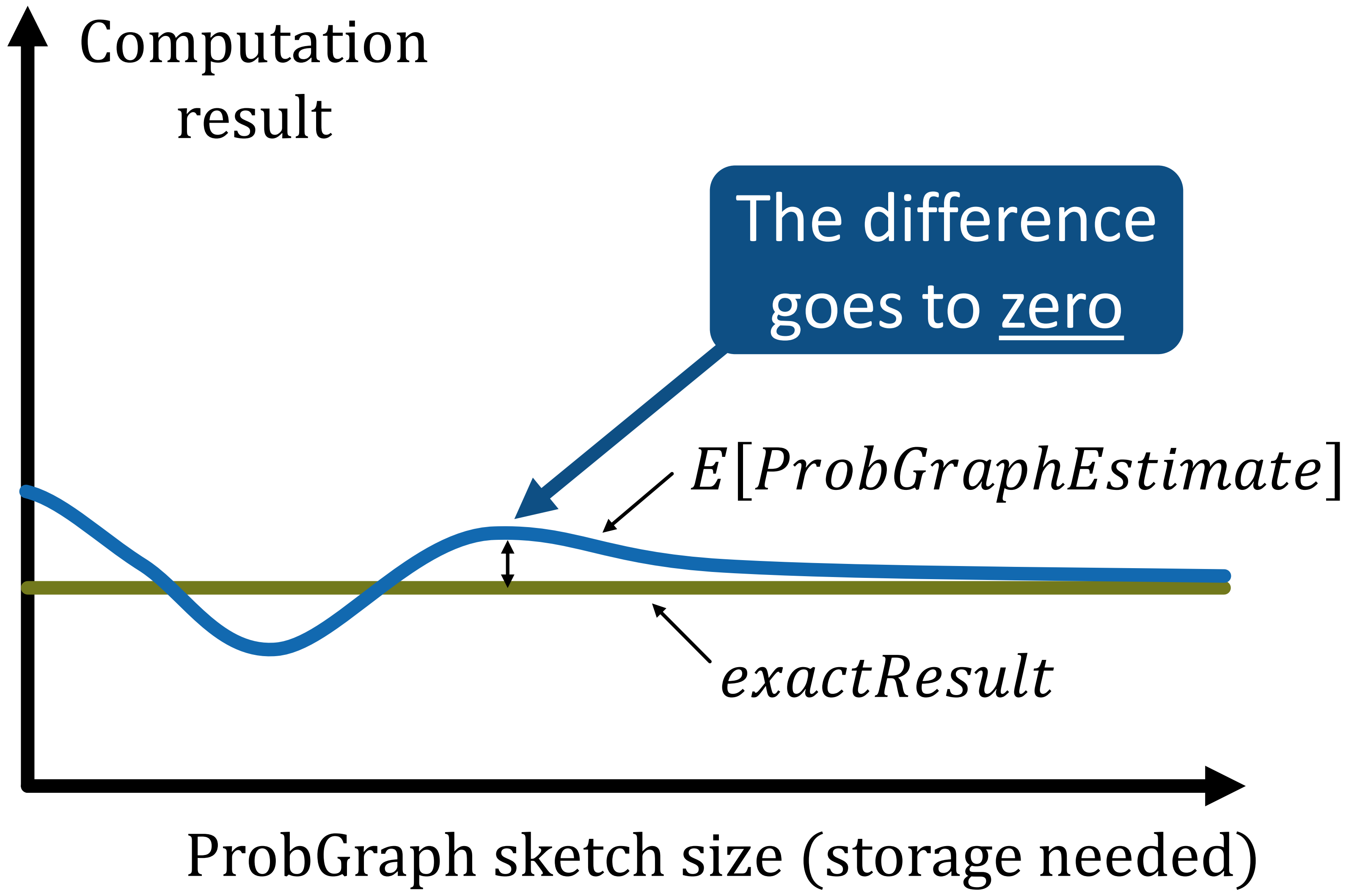
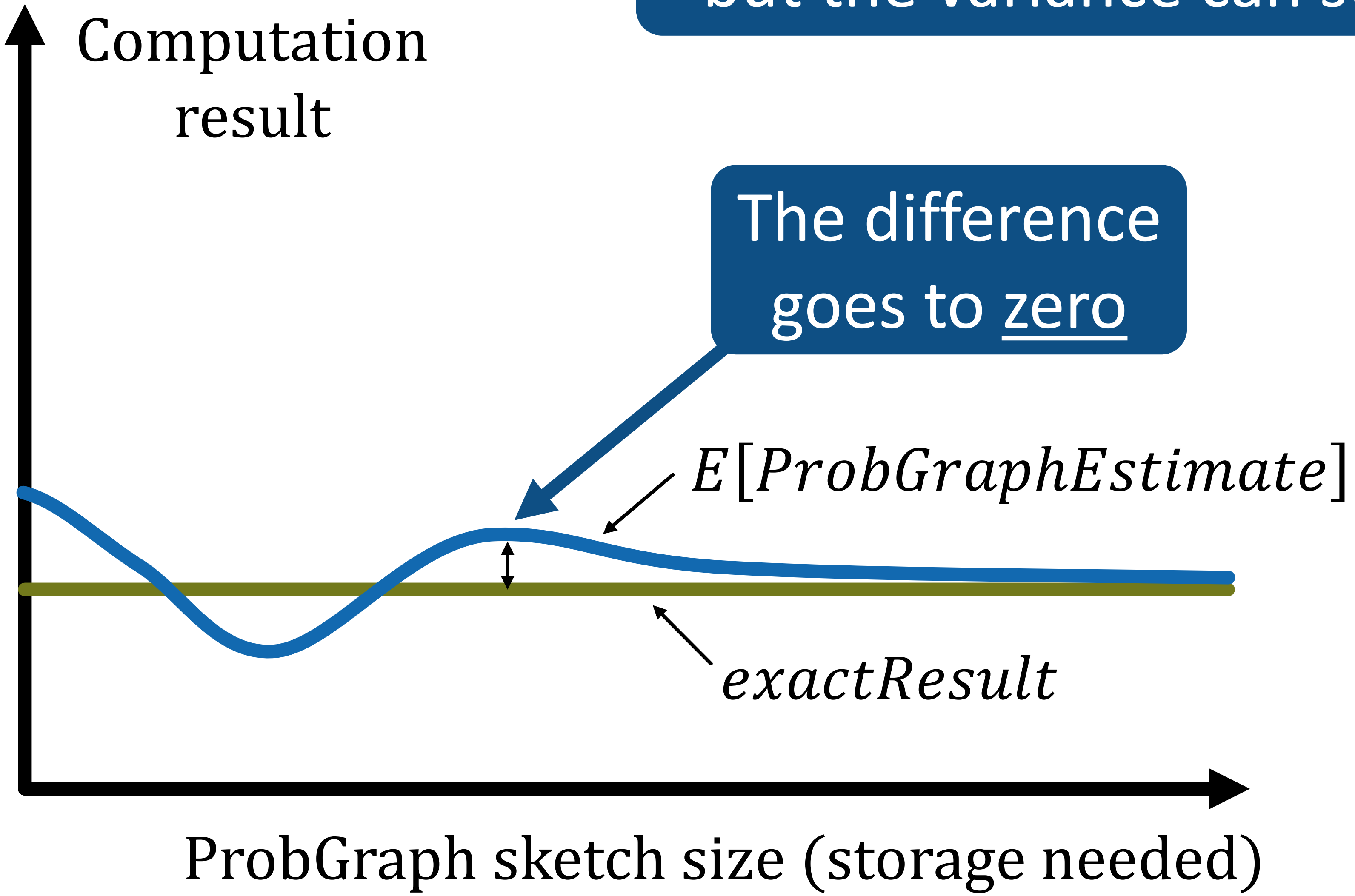
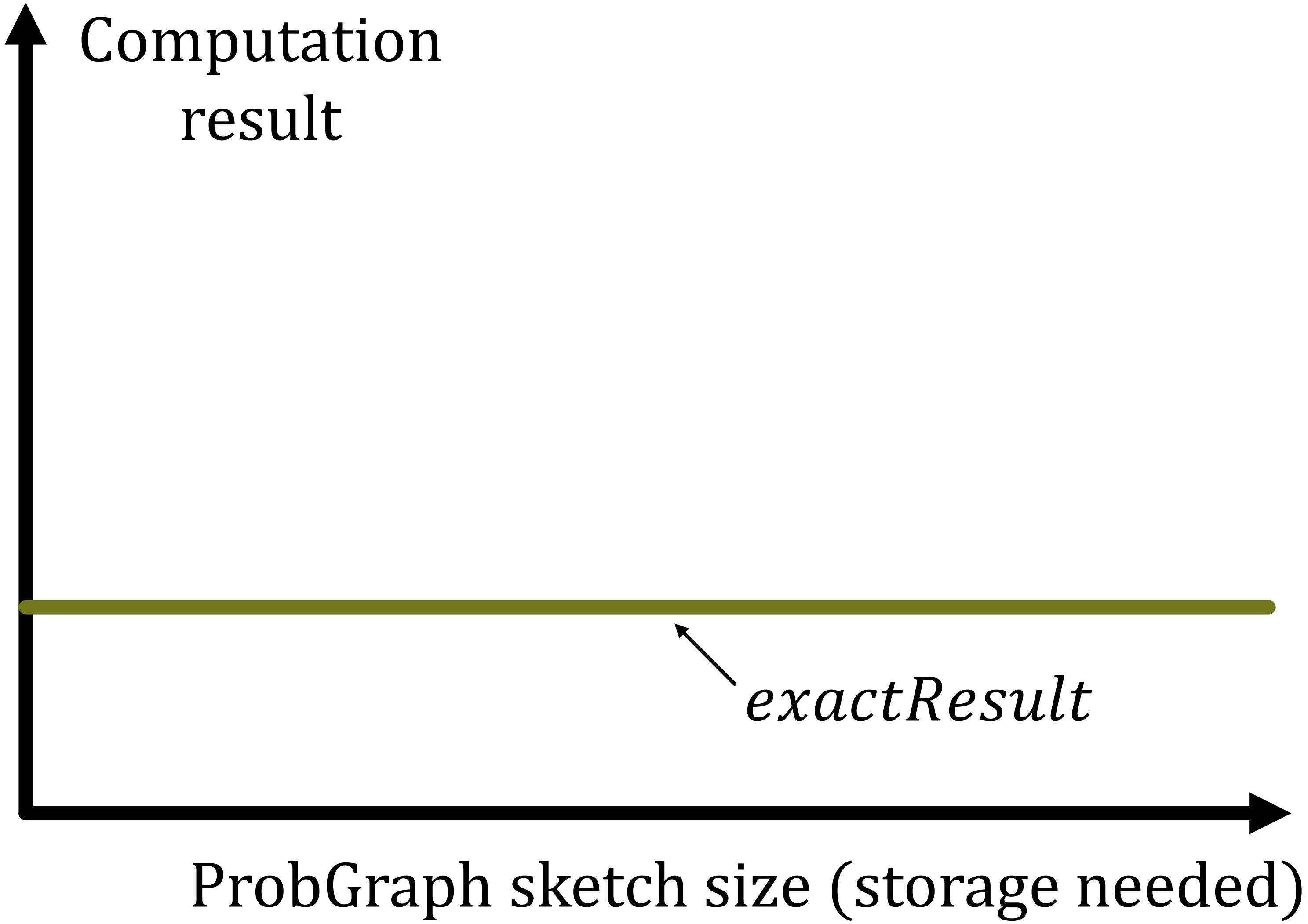


ProbGraph is asymptotically unbiased

Zero average error at some point… but the variance can still go wild



ProbGraph is consistent



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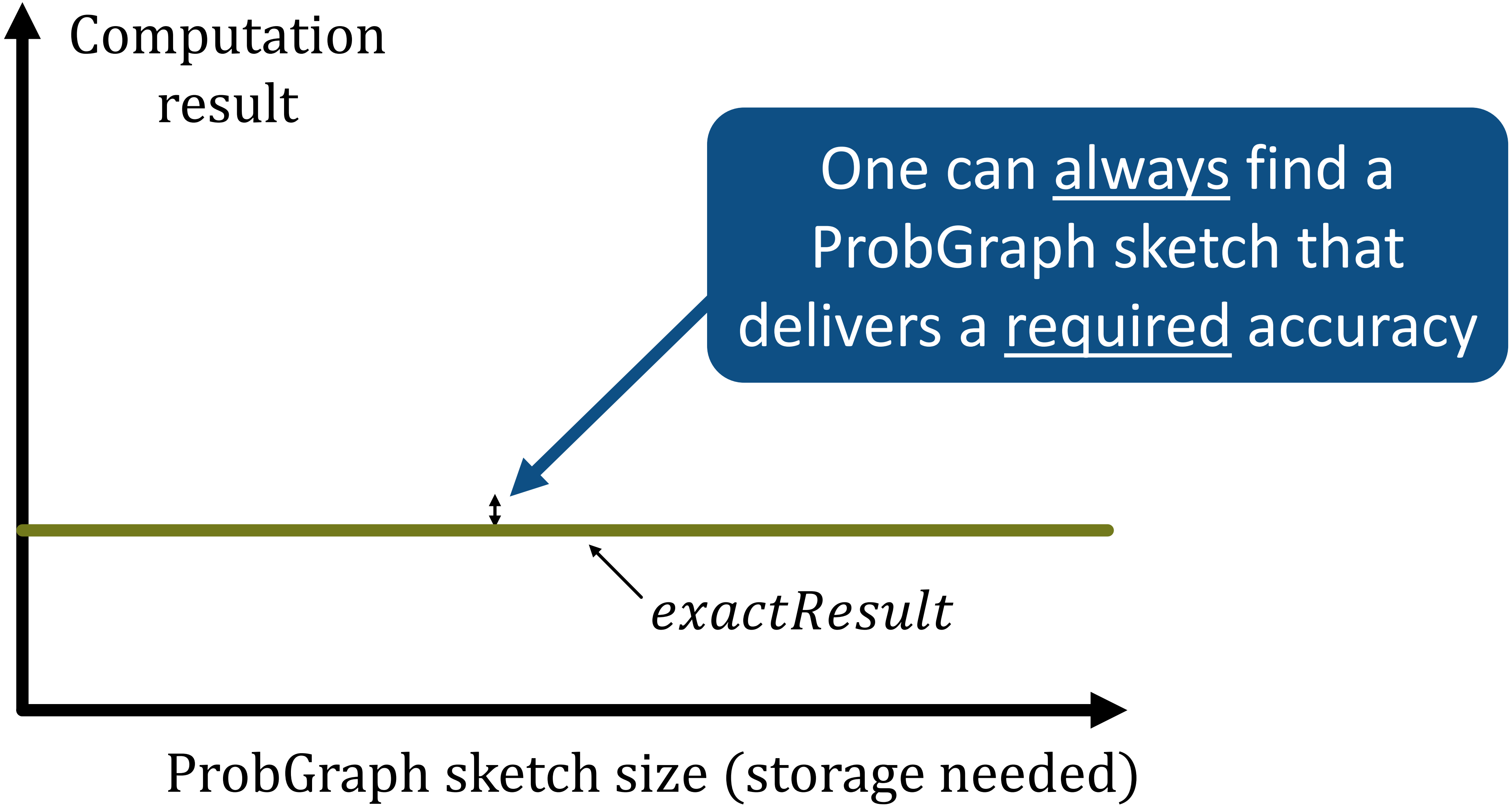

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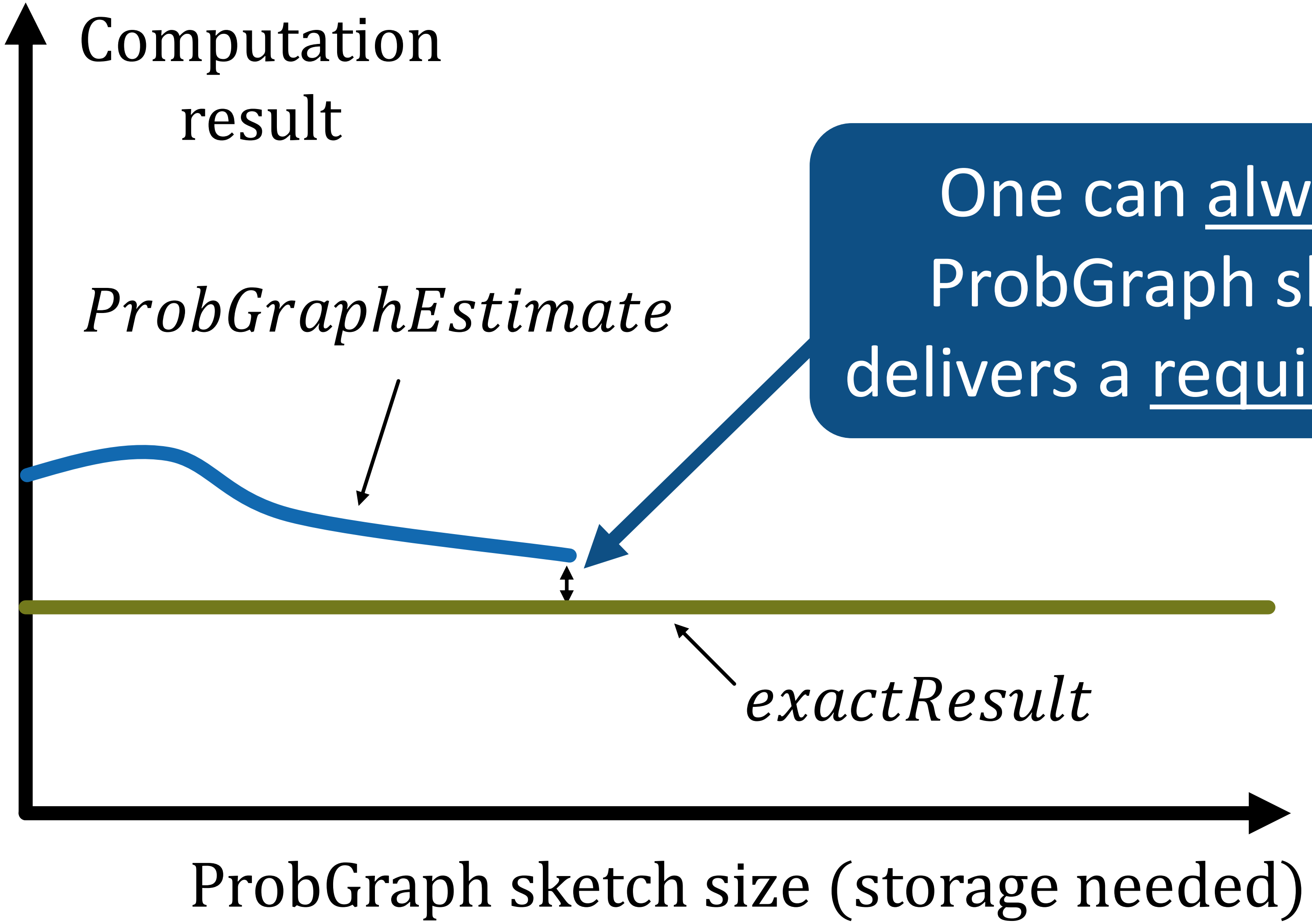
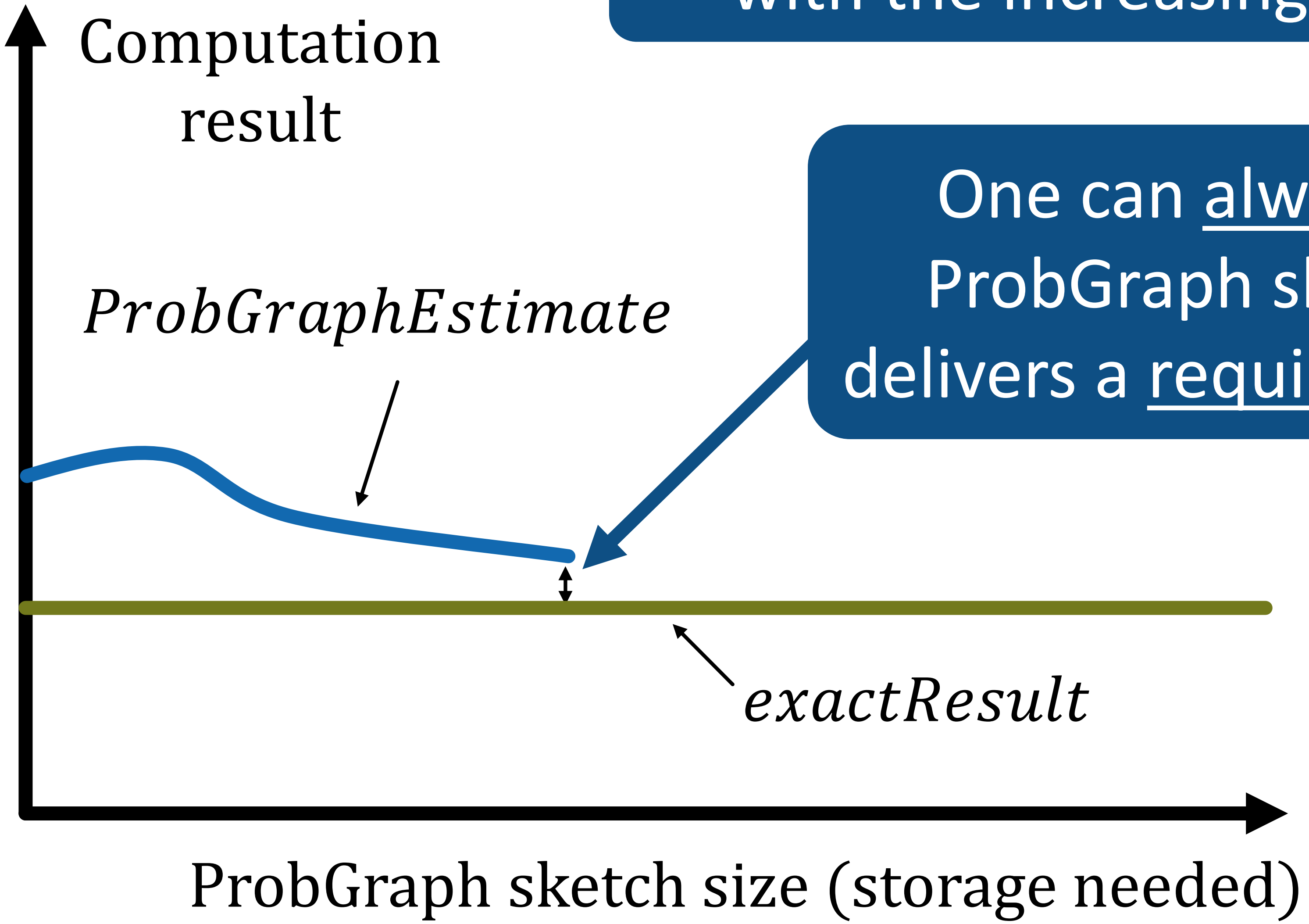


One can always find a ProbGraph sketch that delivers a required accuracy

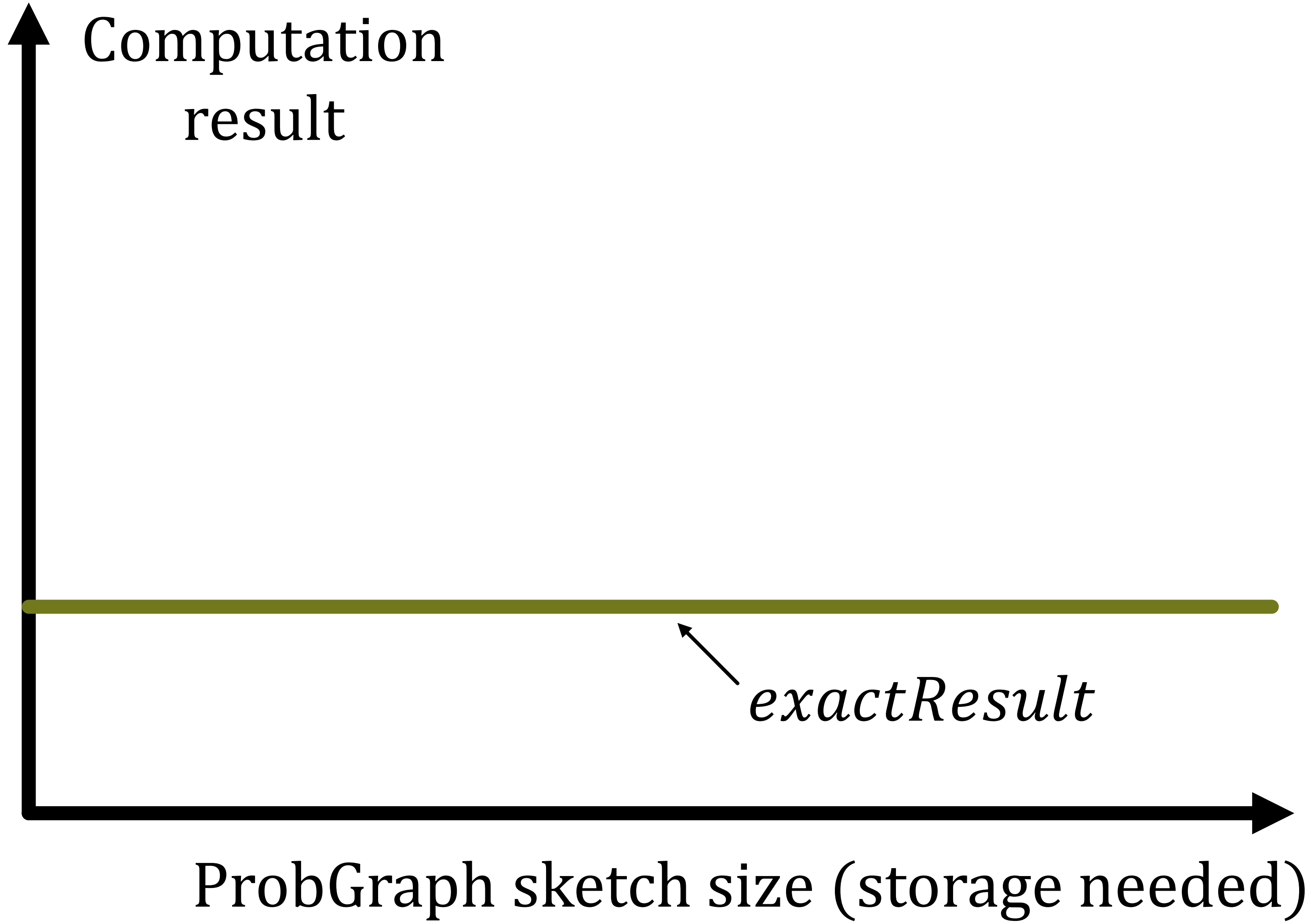
ProbGraph is consistent

The variance also converges to zero with the increasing sketch size



One can always find a ProbGraph sketch that delivers a required accuracy

ProbGraph is asymptotically efficient



ProbGraph is asymptotically efficient

[1] J. Tetek, "Approximate triangle counting via sampling and fast matrix ˇ multiplication", arXiv 2021.
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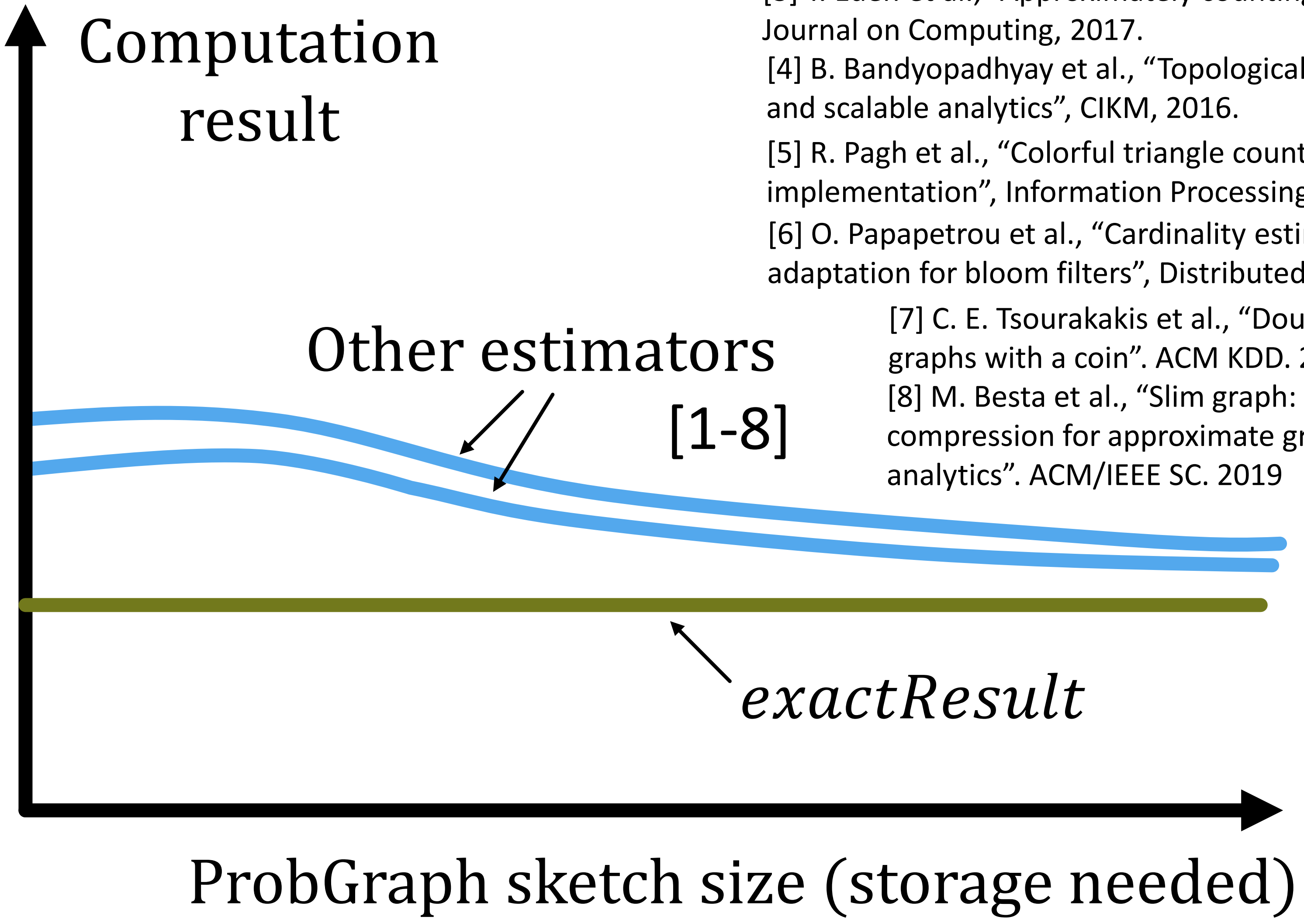

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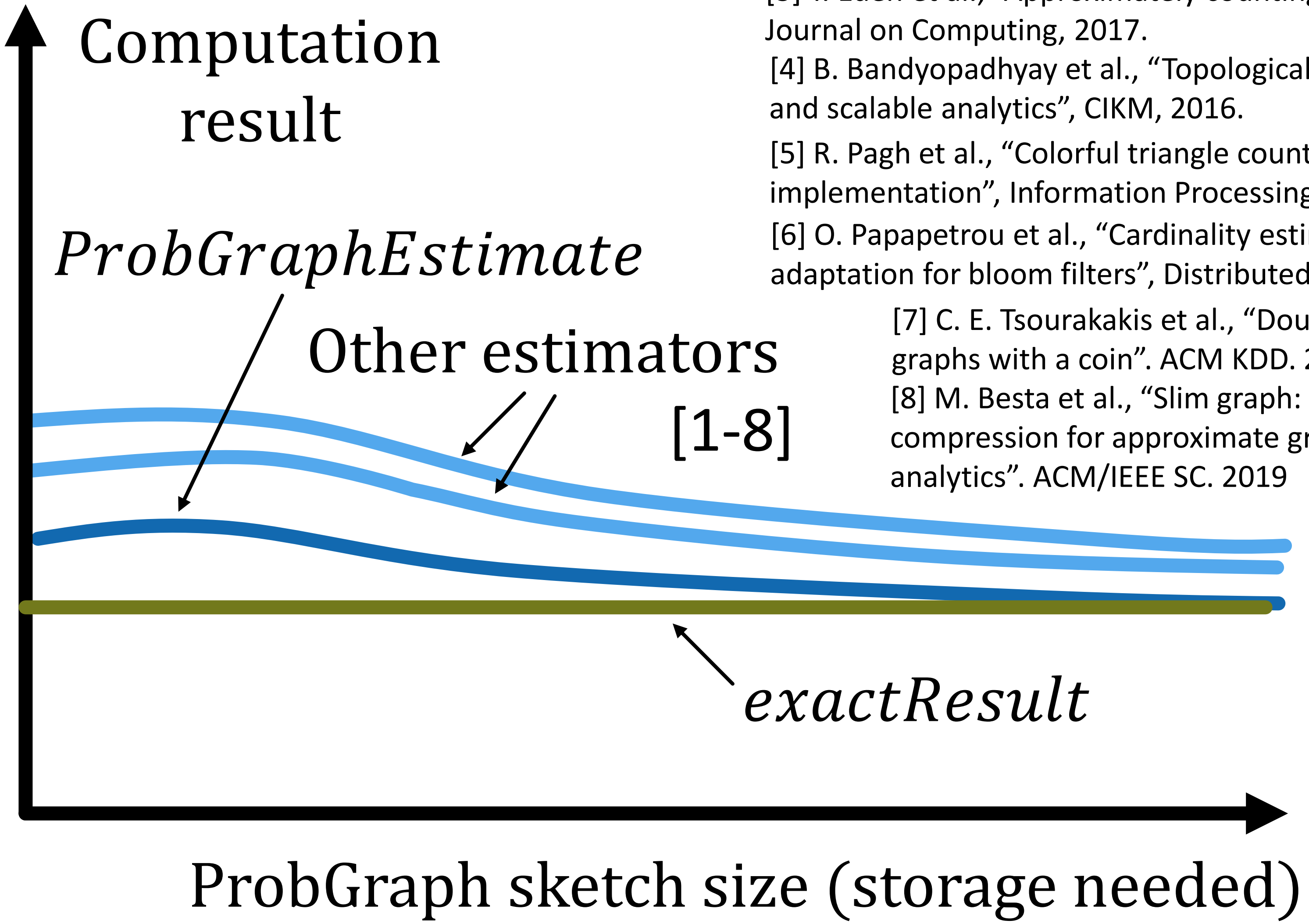

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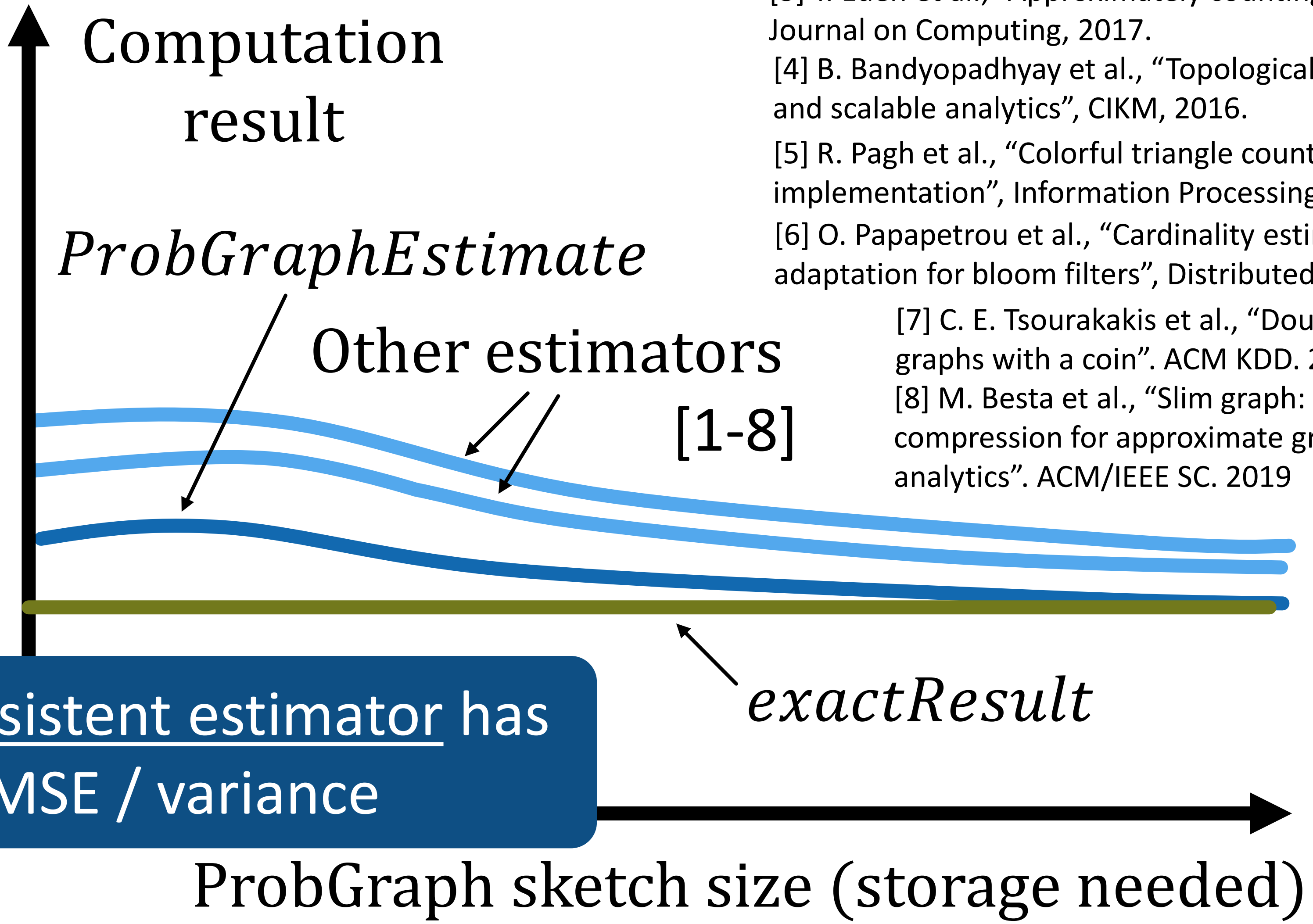

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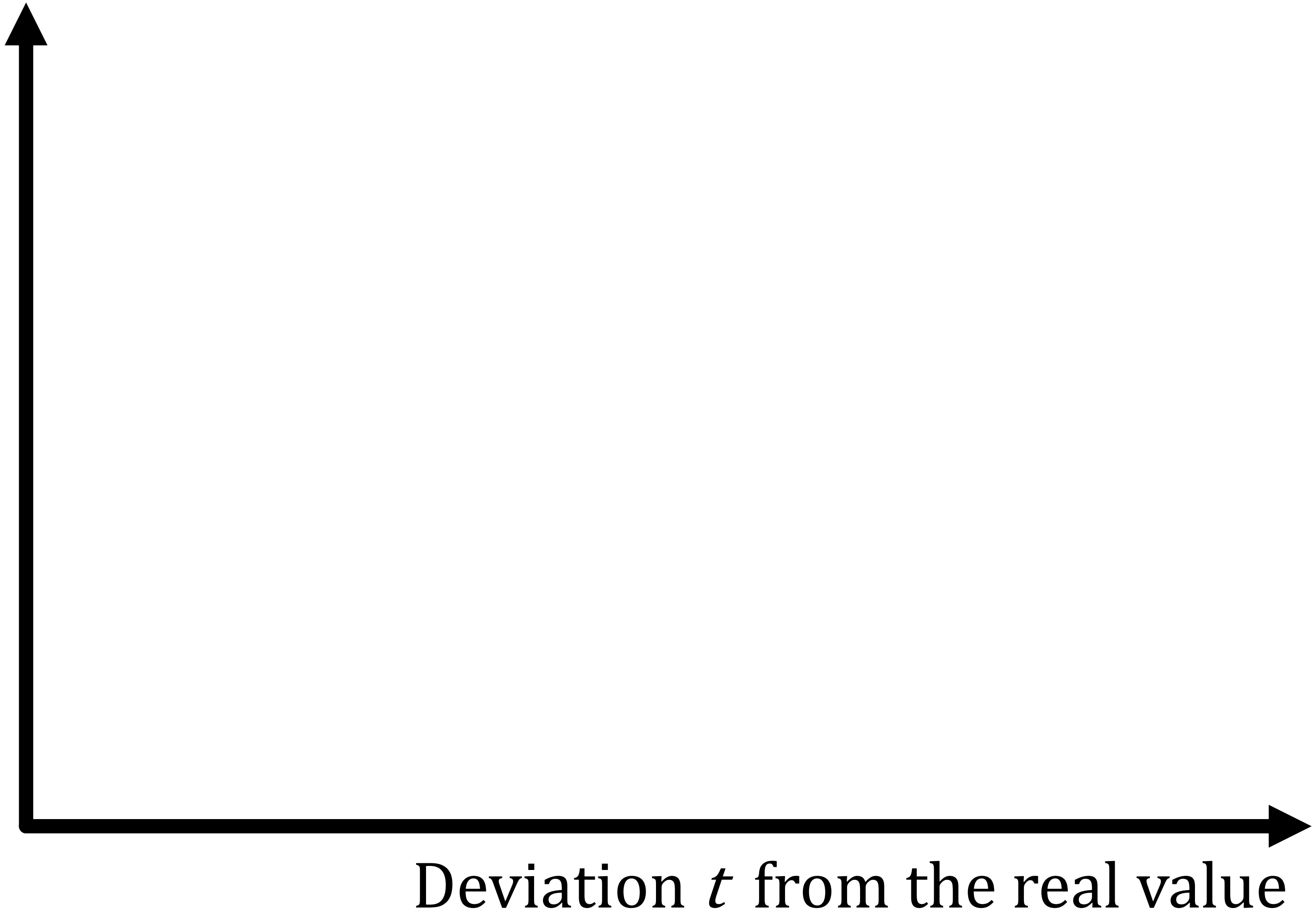
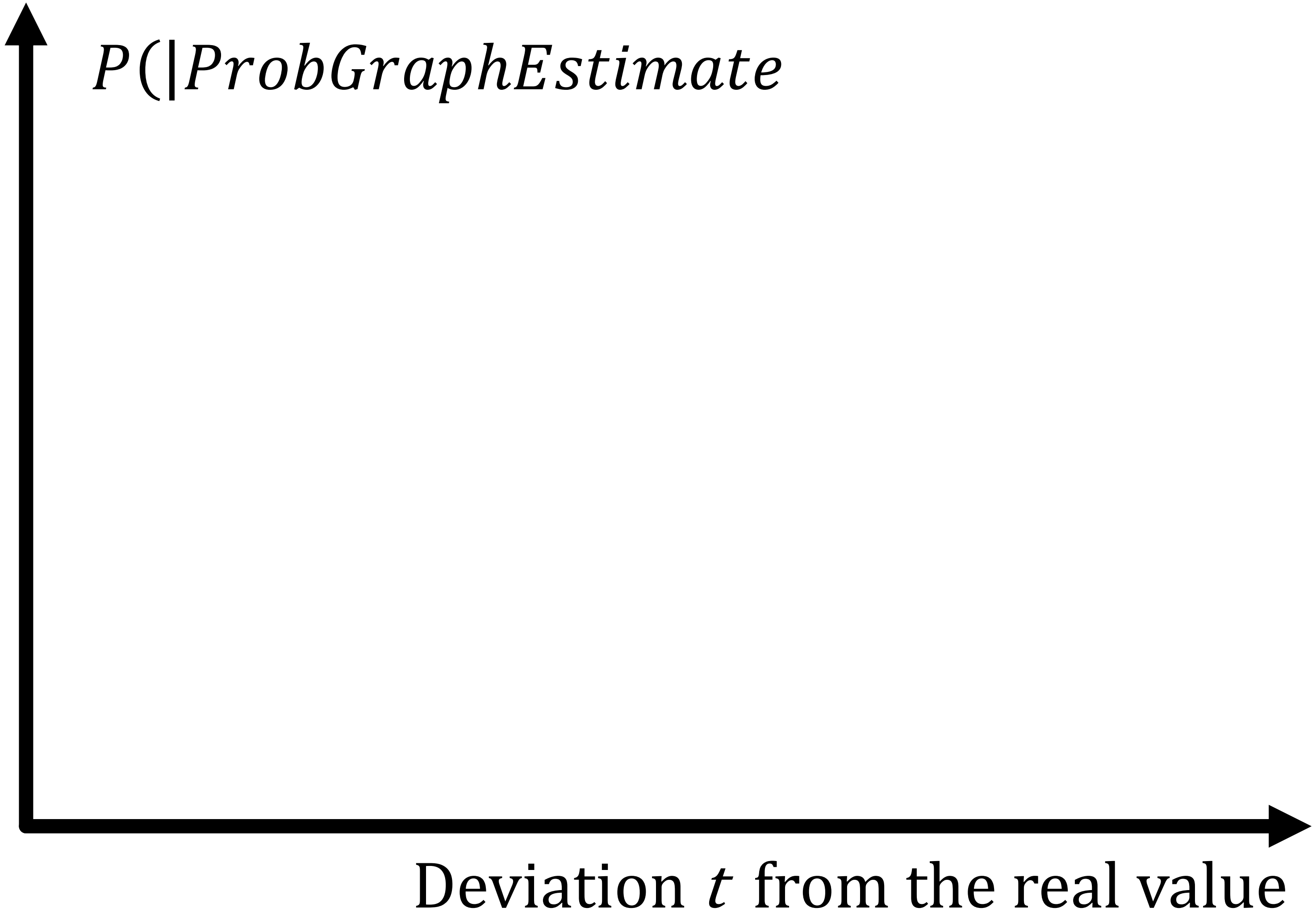
No other consistent estimator has lower MSE / variance

ProbGraph has strong concentration bounds

ProbGraph has <u>strong concentration bounds</u>



ProbGraph has <u>strong concentration bounds</u>



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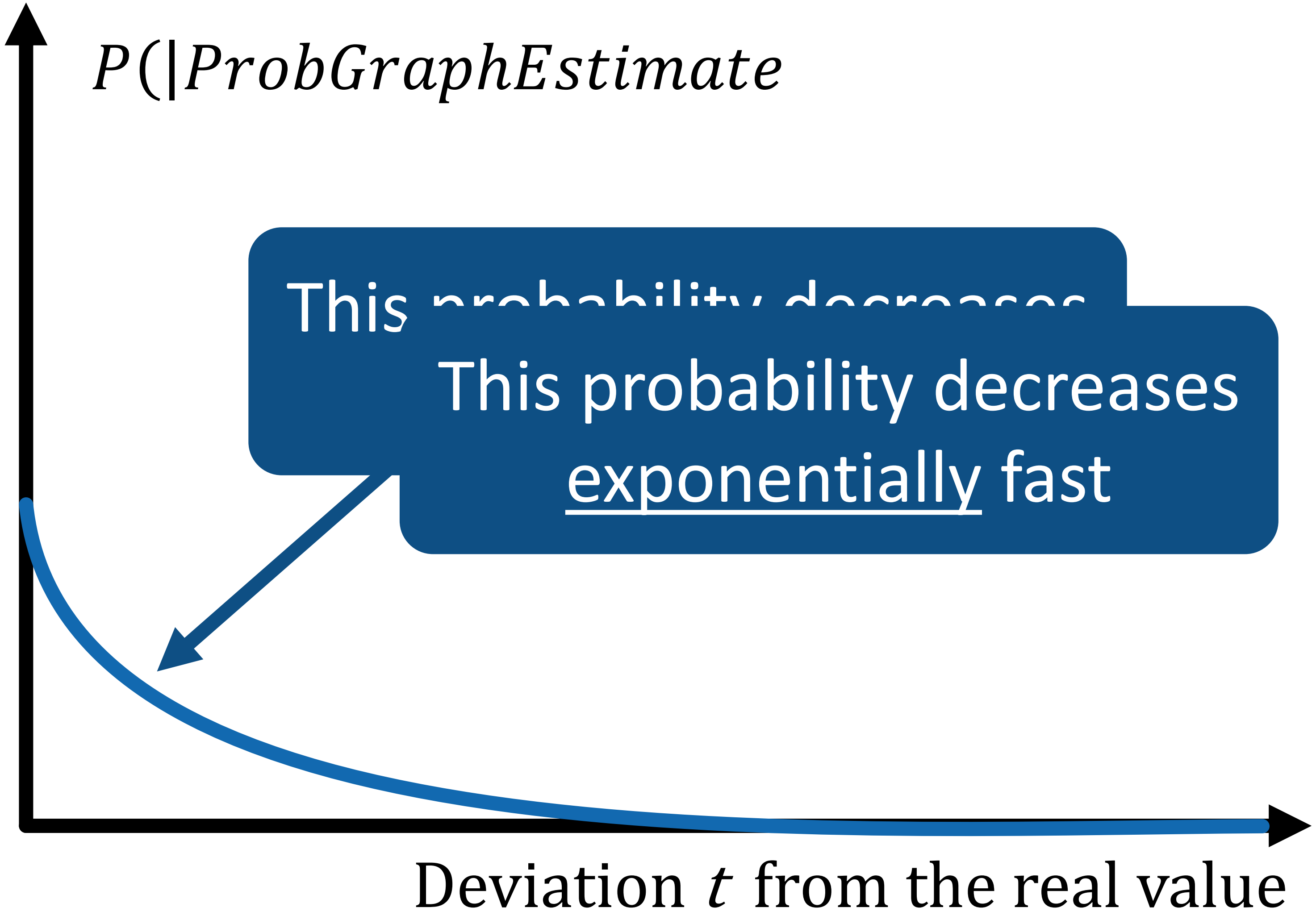
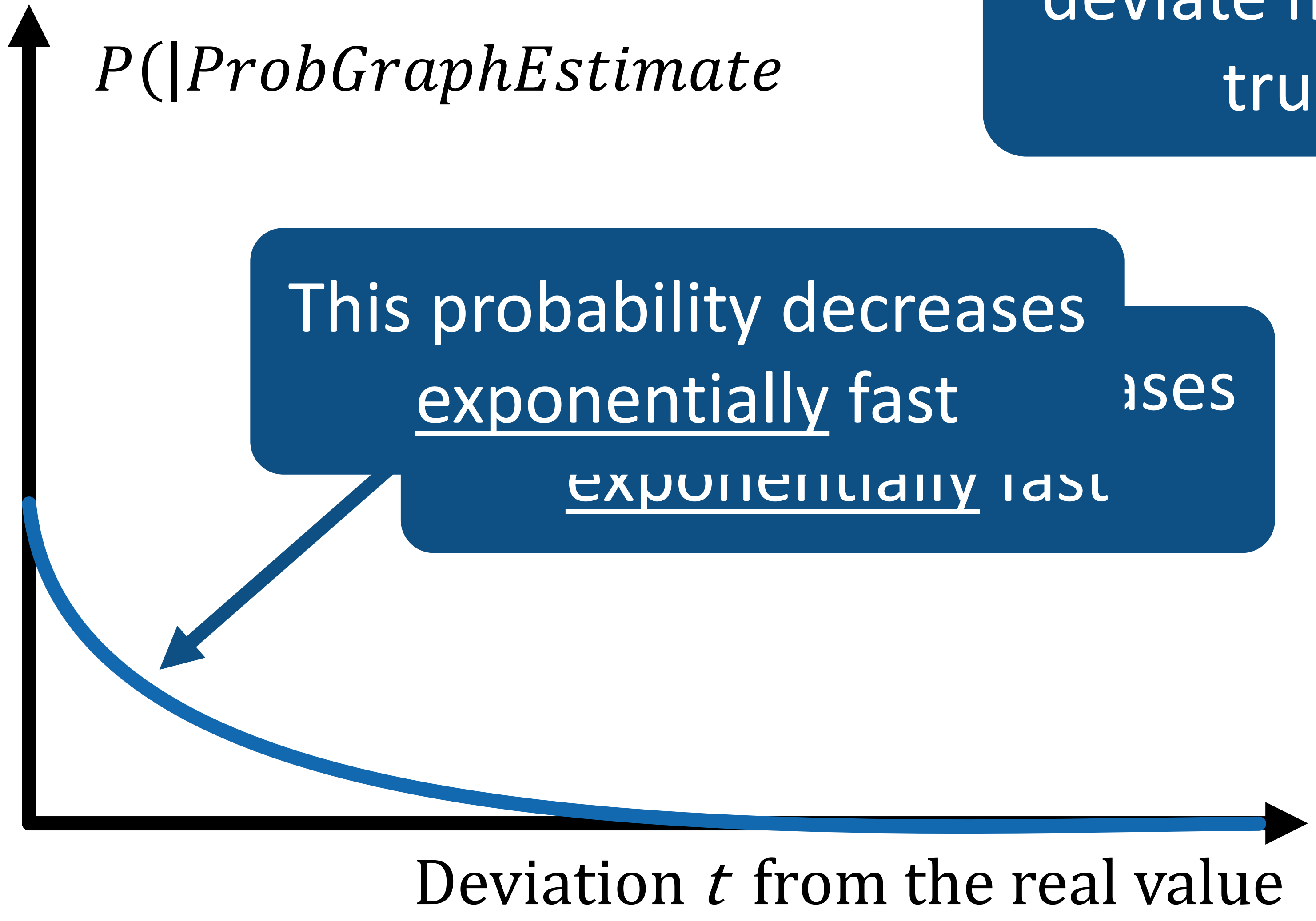


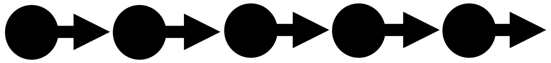
ProbGraph has strong concentration bounds

ProbGraph is unlikely to deviate much from the true values

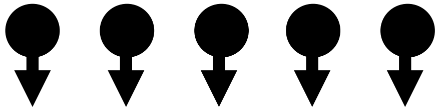


This probability decreases exponentially fast

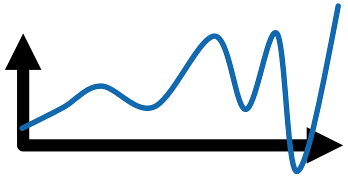
Approximate Graph Processing: Our Objectives



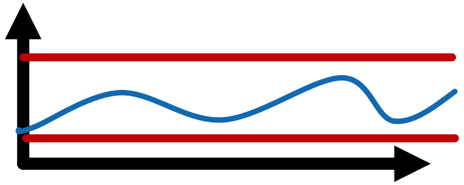
Little parallelism → Rich parallelism



Specific → Wide applicability



No/loose accuracy guarantees → Strong accuracy guarantees



Slow → High performance

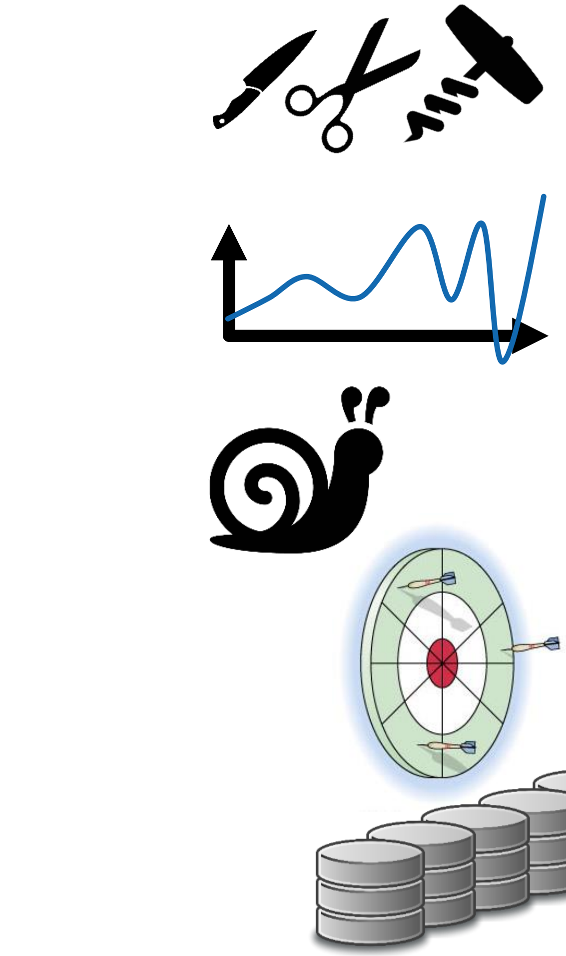
Low accuracy → High accuracy

Large memory overheads → Low & controllable memory overheads

Approximate Graph Processing: Our Objectives

Current	Objective
Little parallelism	Rich parallelism
Specific	Wide applicability
No/loose accuracy guarantees	Strong accuracy guarantees
Slow	High performance
Low accuracy	High accuracy
Large memory overheads	Low & controllable memory overheads

Approximate Graph Processing: Our Objectives



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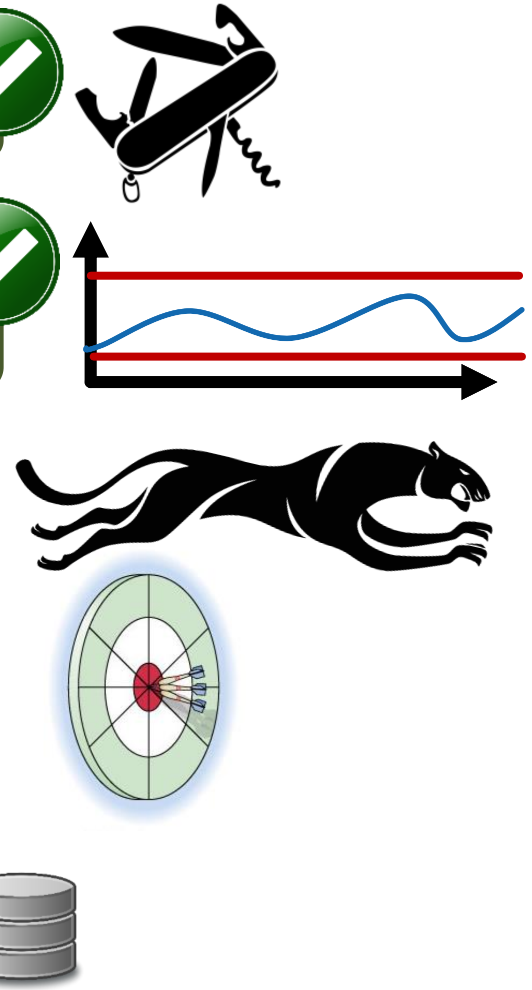

Evaluation: Used Machines & Objectives

Evaluation: Used Machines & Objectives

**CSCS Cray Piz Daint,
64 GB per compute node**

Evaluation: Used Machines & Objectives

Dell PowerEdge R910 server

CSCS Cray Piz Daint,
64 GB per compute node

Evaluation: Used Machines & Objectives

Goal: One design with…

<u>large</u> speedups +

<u>small & controlled</u> accuracy loss +

<u>small & controlled</u> memory requirements

Dell PowerEdge R910 server

CSCS Cray Piz Daint,
64 GB per compute node

Considered Graph Datasets

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67 graph datasets,
15 areas,
5 major graph
dataset repositories

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67 graph datasets,
15 areas,
5 major graph
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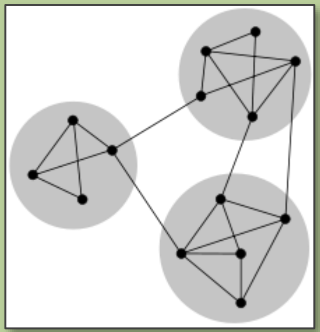
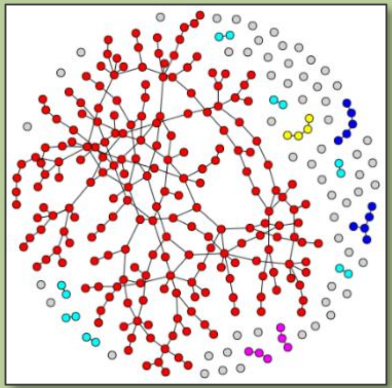
Synthetic graphs



Kronecker [1]

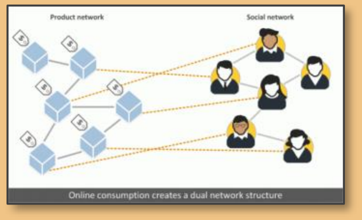


Erdös-Rényi [2]

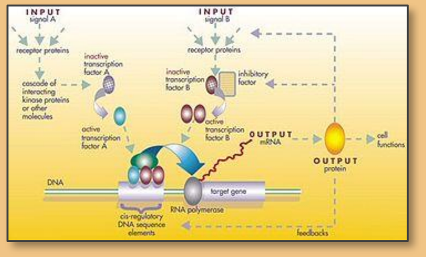
Real-world graphs

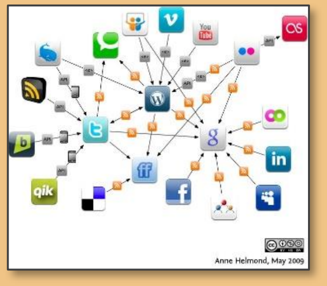
Social networks

Purchases



Gene functions

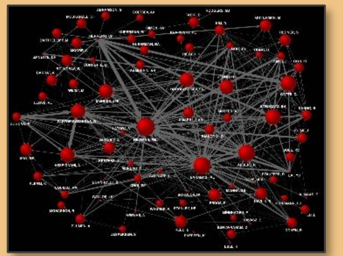




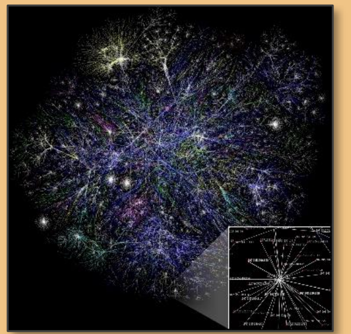
Communication

Road nets

Brain structure

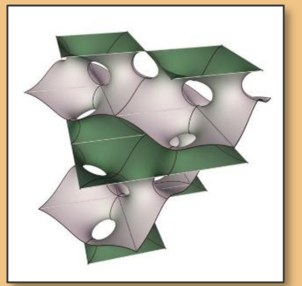


Citation graphs

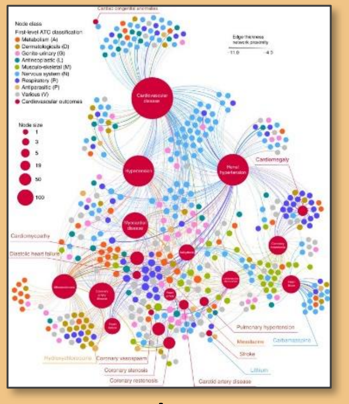


Web graphs

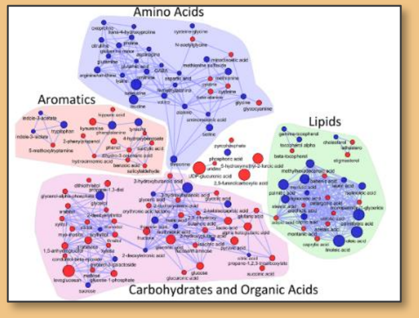
Compute graphs



Mathematics



Medicine



Chemistry

Economic nets

[1] J. Leskovec et al. Kronecker Graphs: An Approach to Modeling Networks. J. Mach. Learn. Research. 2010.
[2] P. Erdos and A. Renyi. On the evolution of random graphs. Pub. Math. Inst. Hun. A. Science. 1960.

Considered Graph Datasets

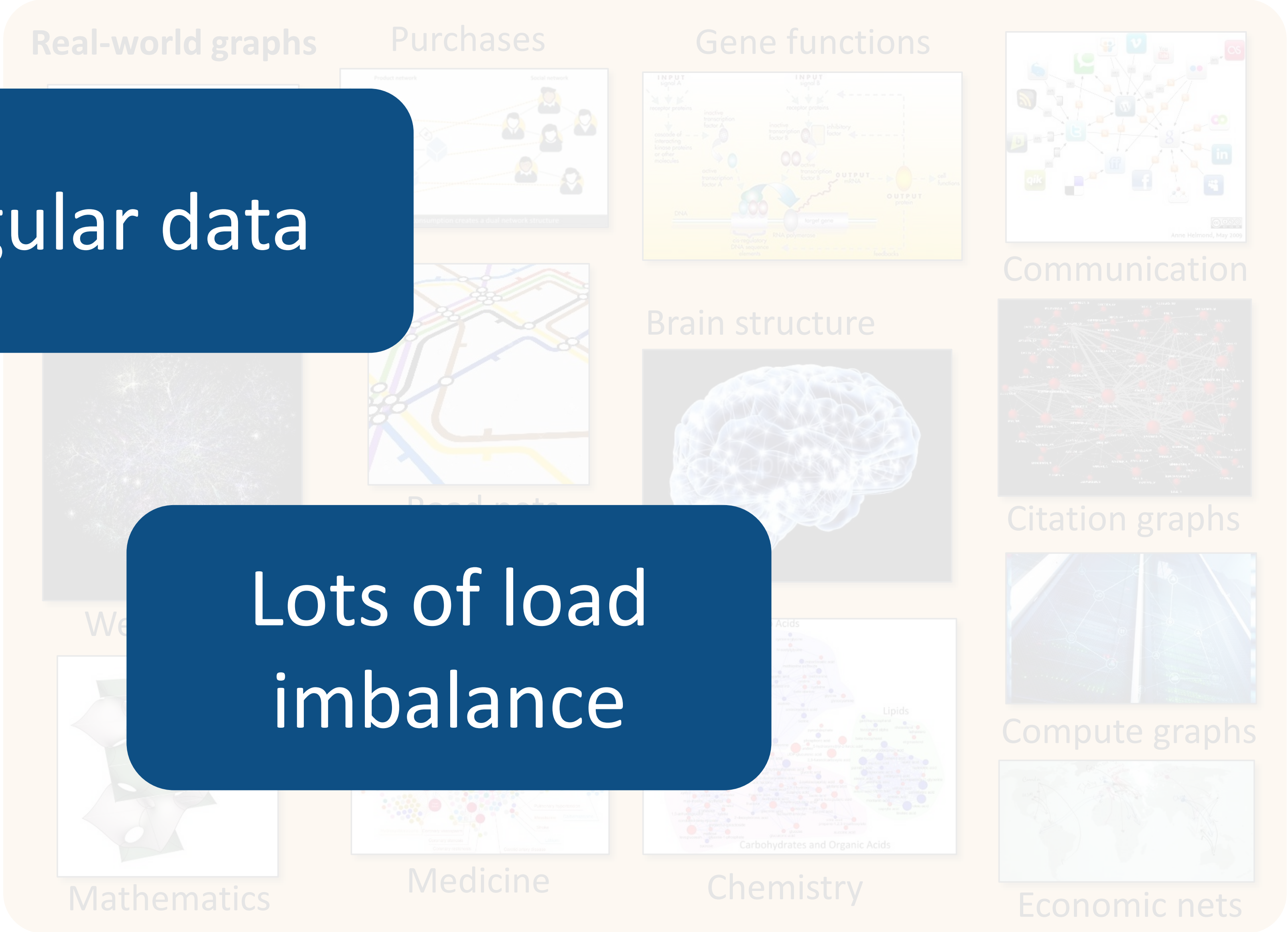
67

5

dataset repositories

Highly irregular data

Lots of load imbalance



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Triangle Counting

Cores/threads: 32
Max memory overhead: 20%

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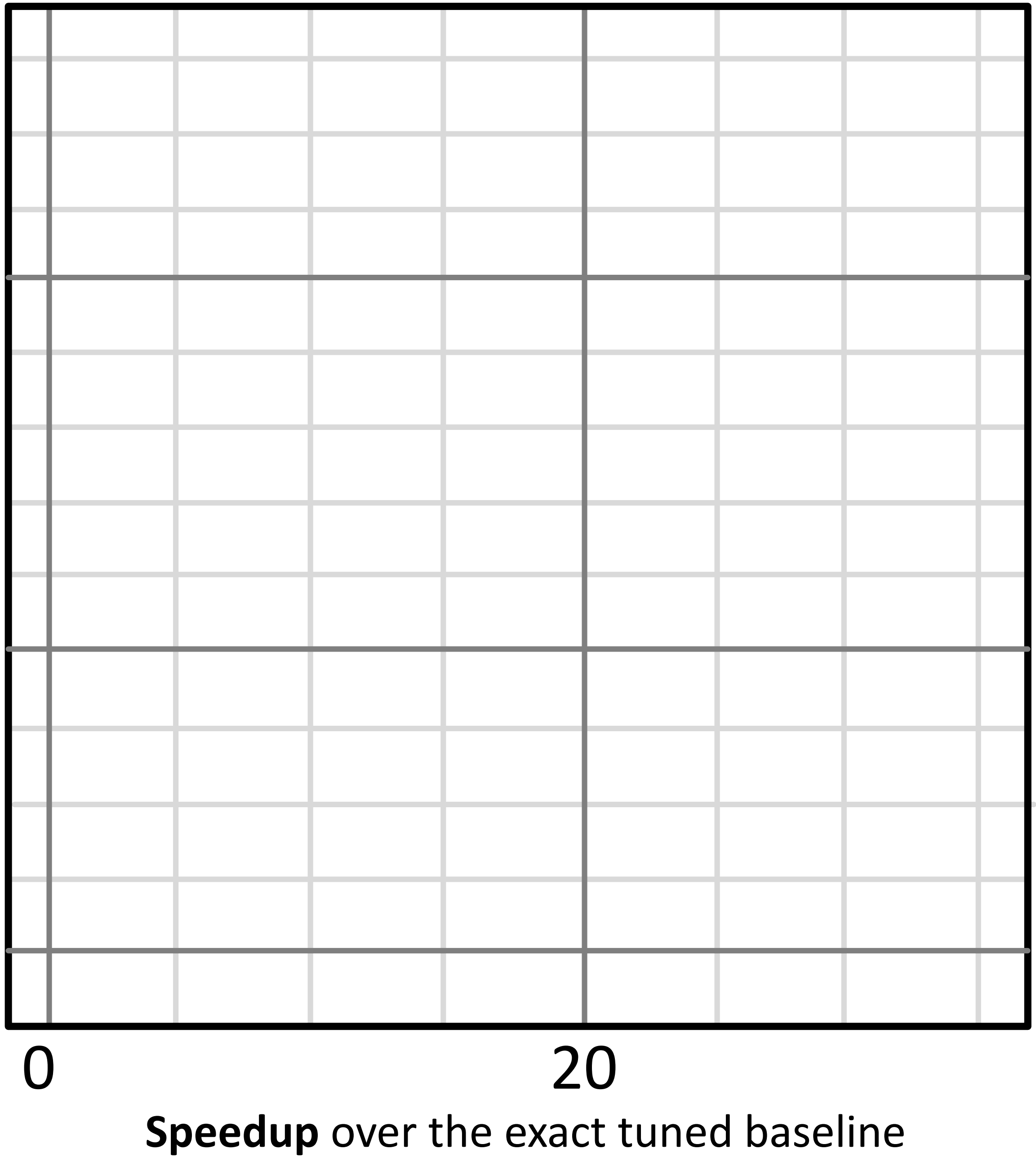

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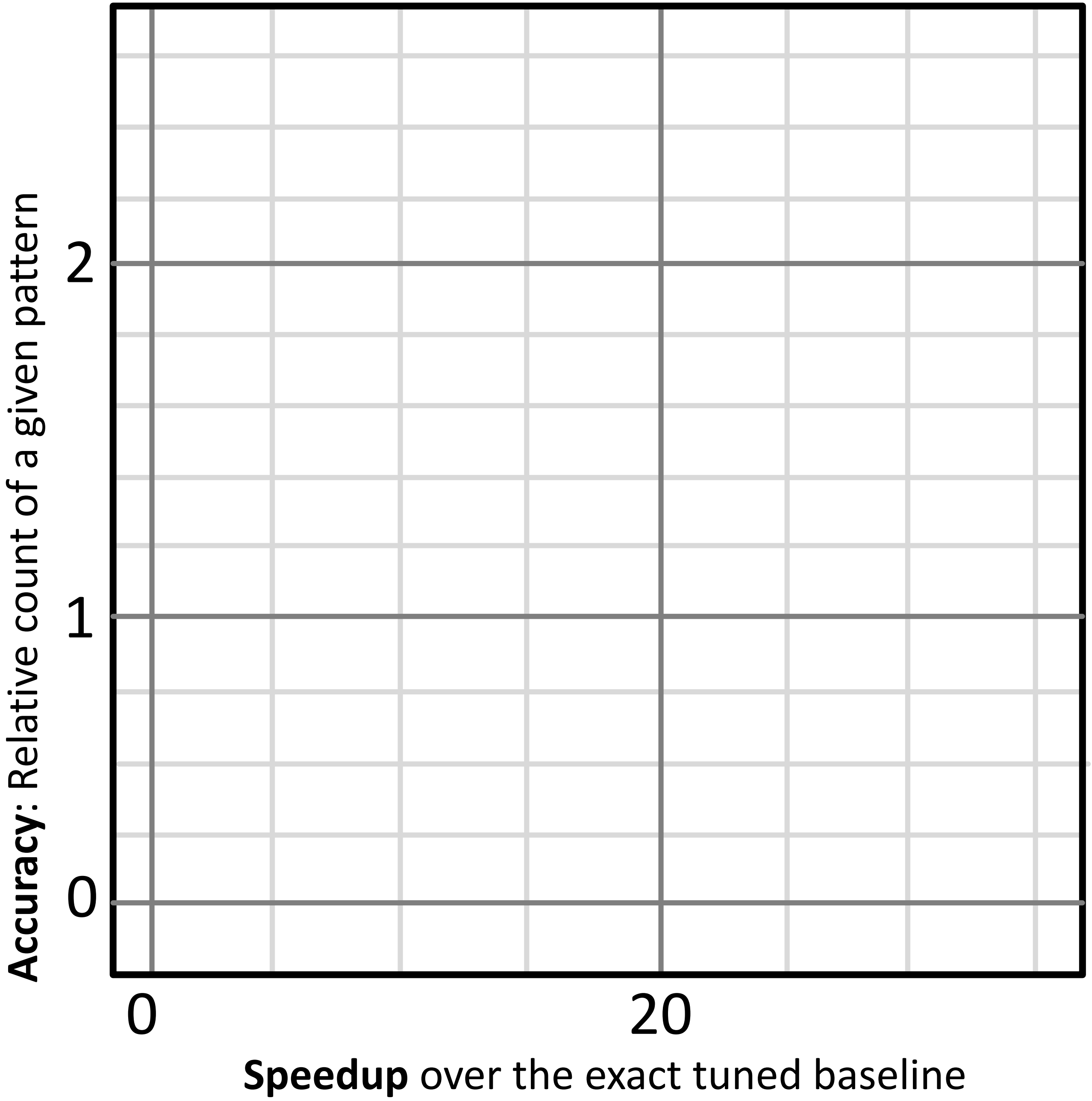

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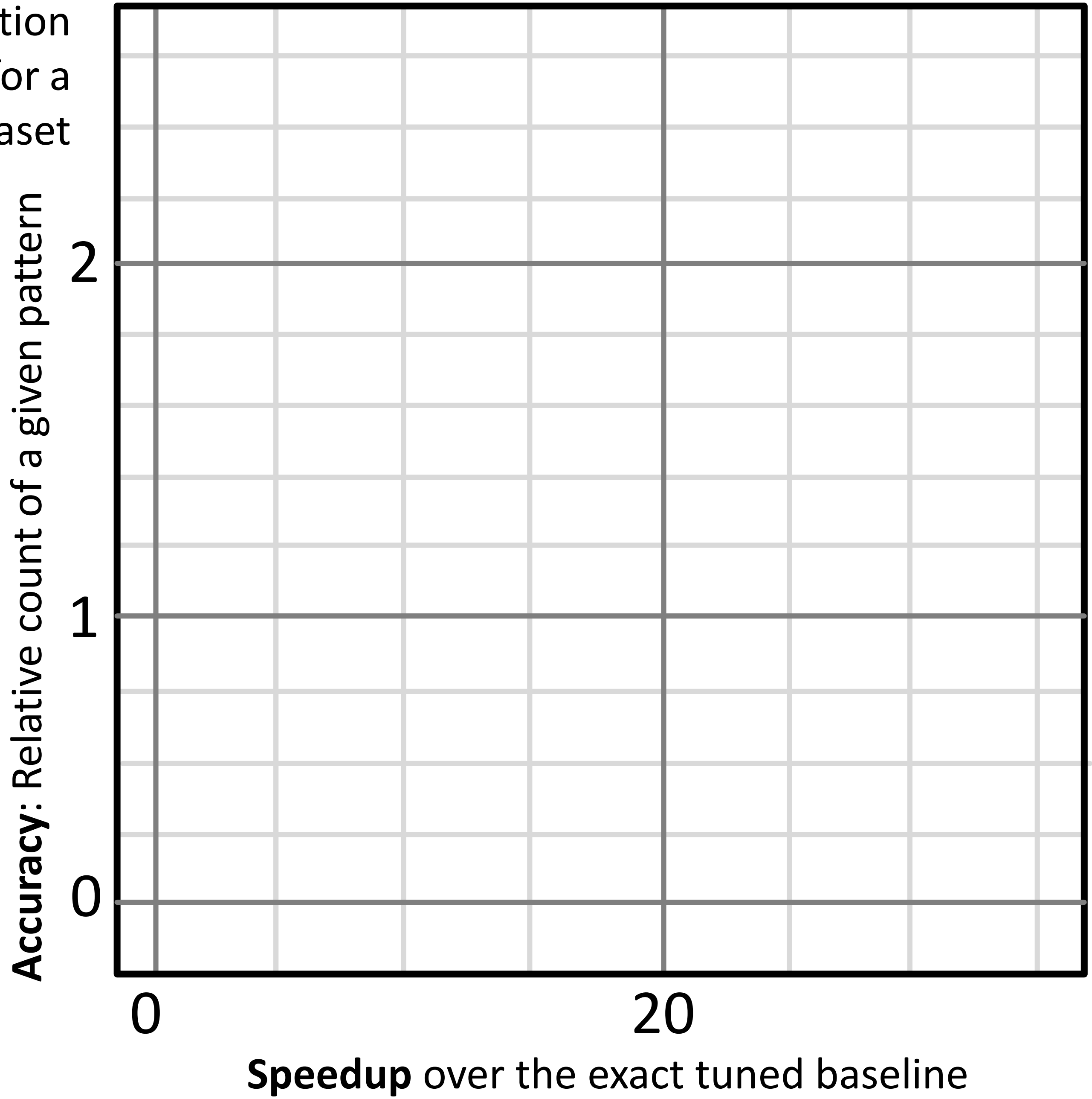
Each data point: the execution of a given scheme for a specific graph dataset



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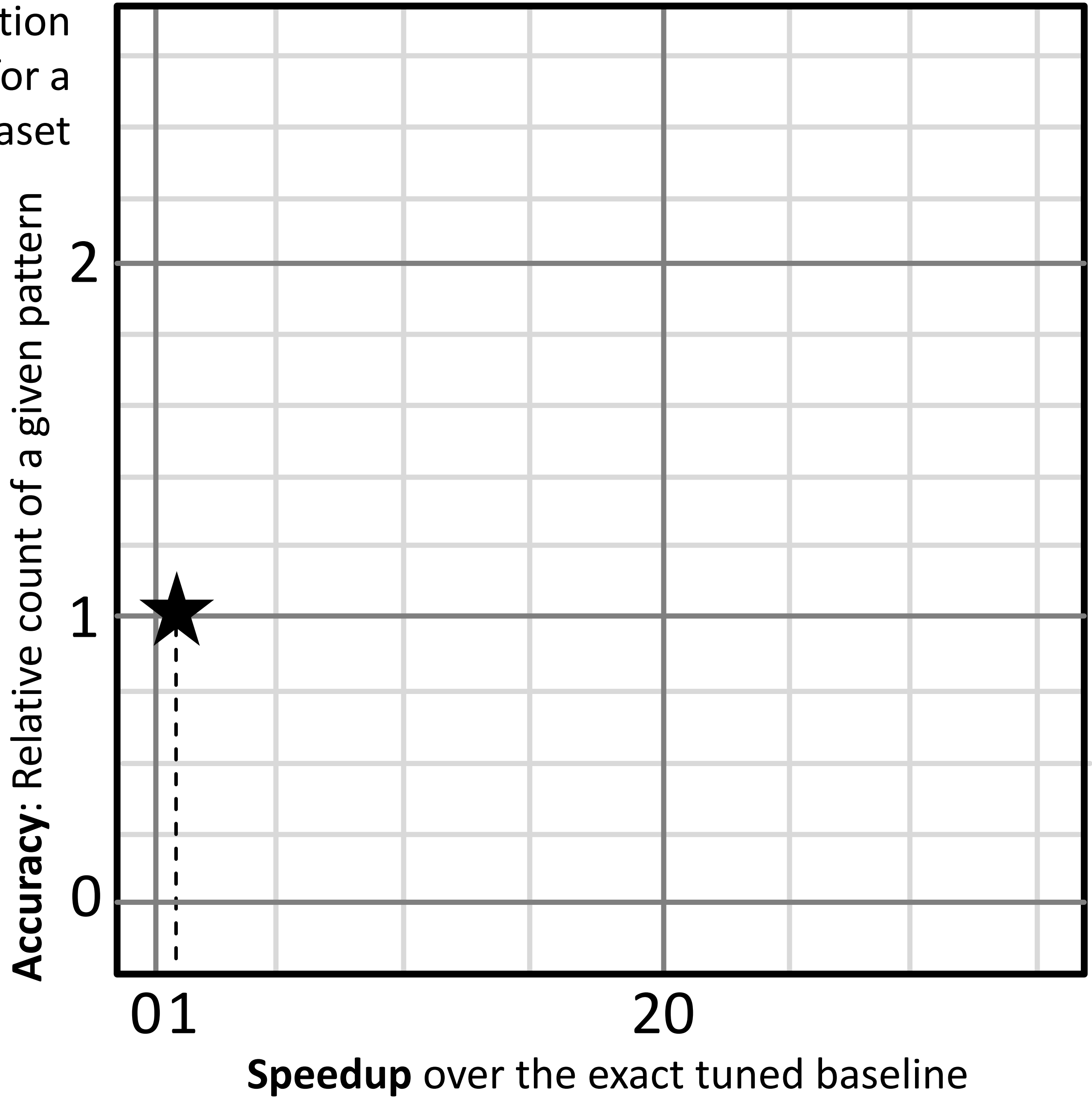
★ Exact baseline [1]



[1] S. Beamer et al., „The GAP Benchmark Suite”. 2015

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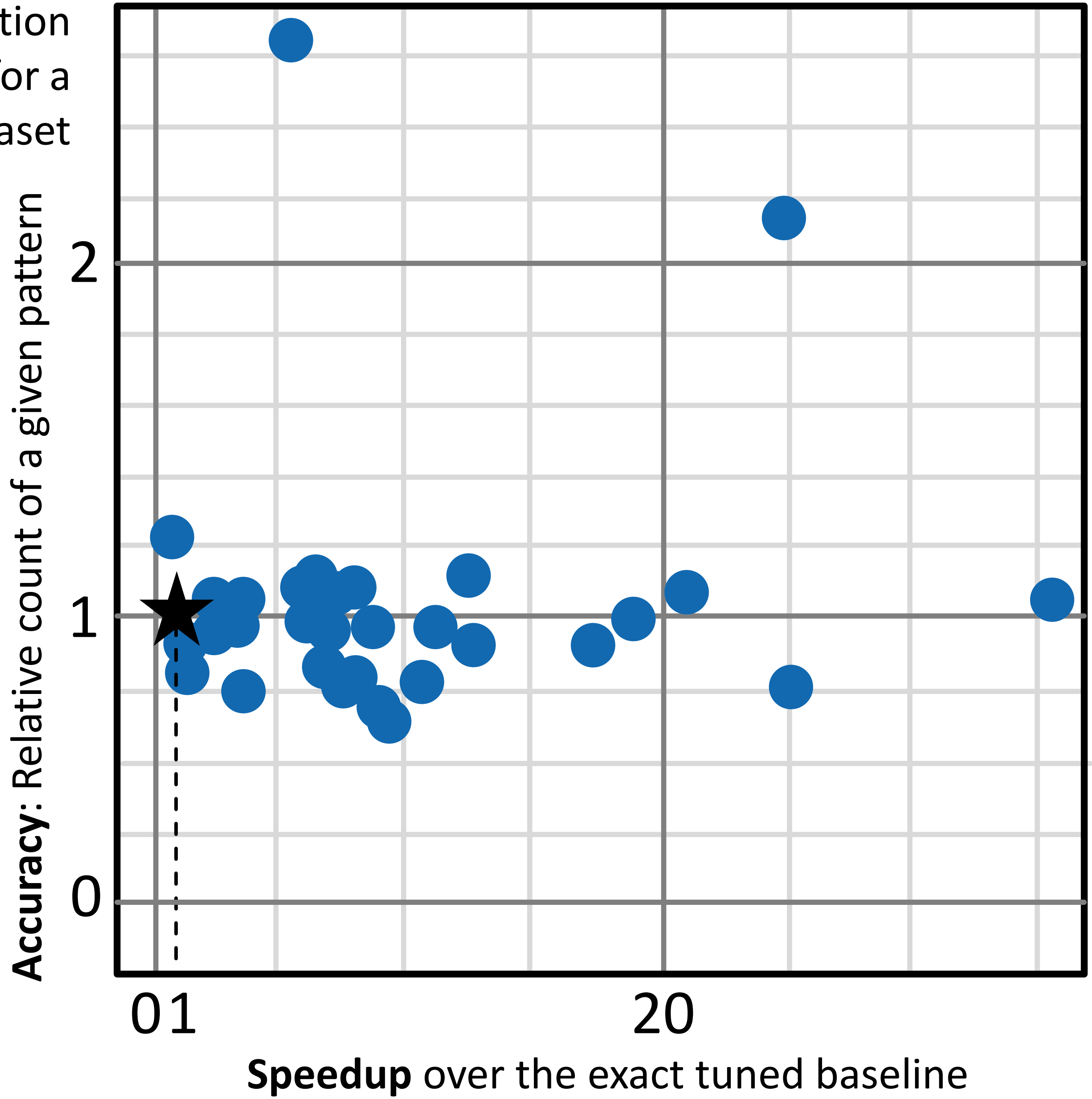

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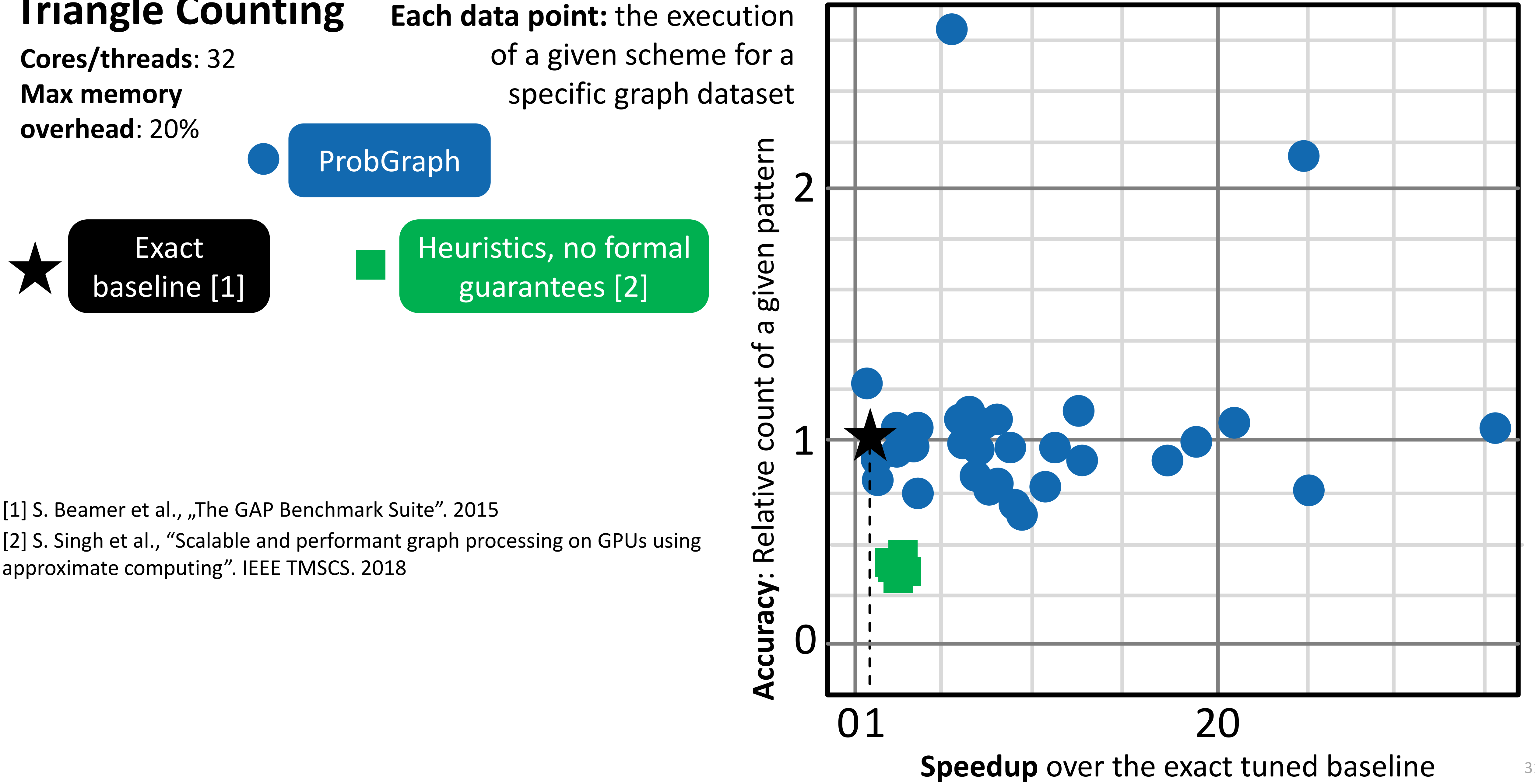

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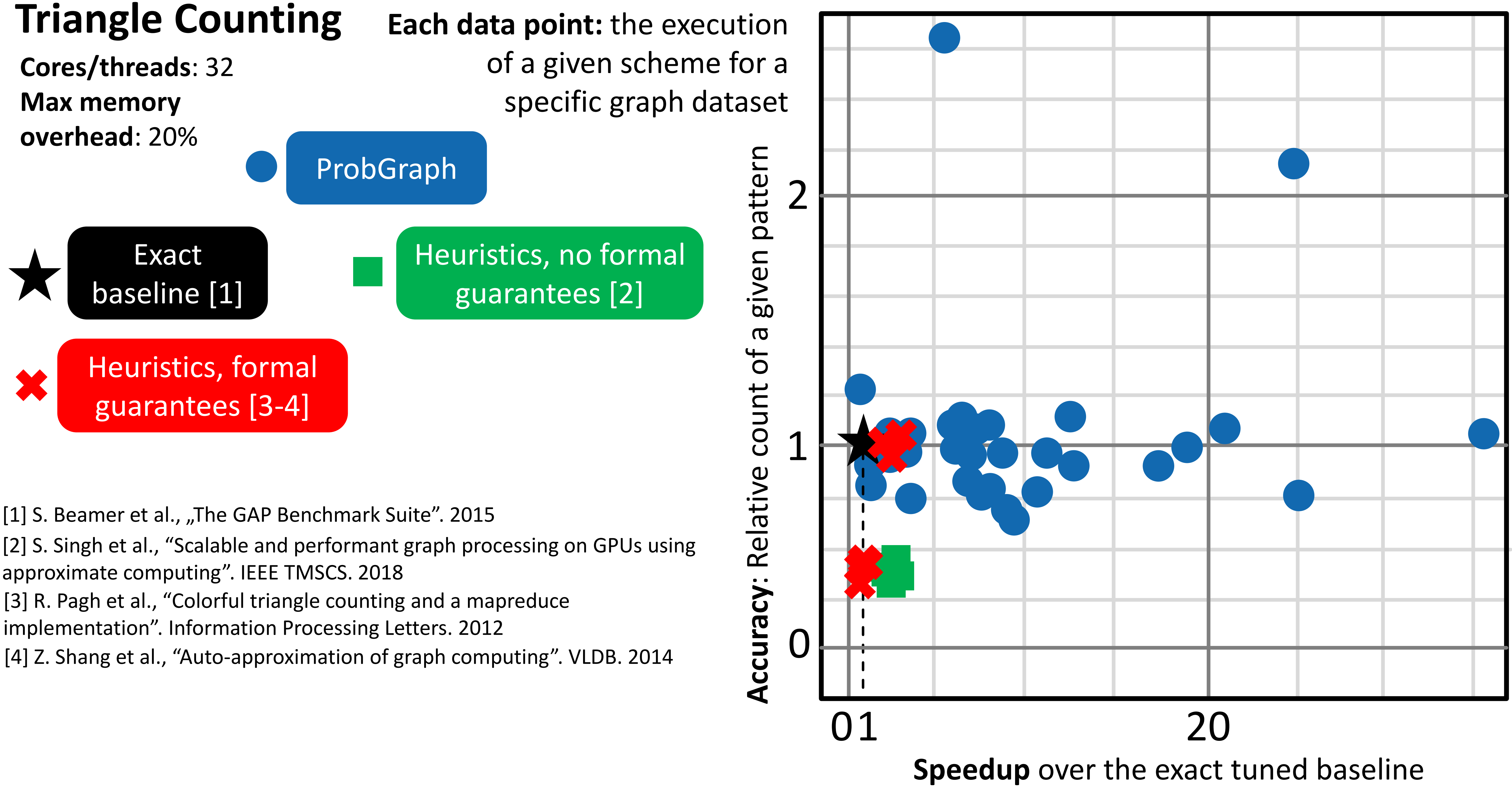

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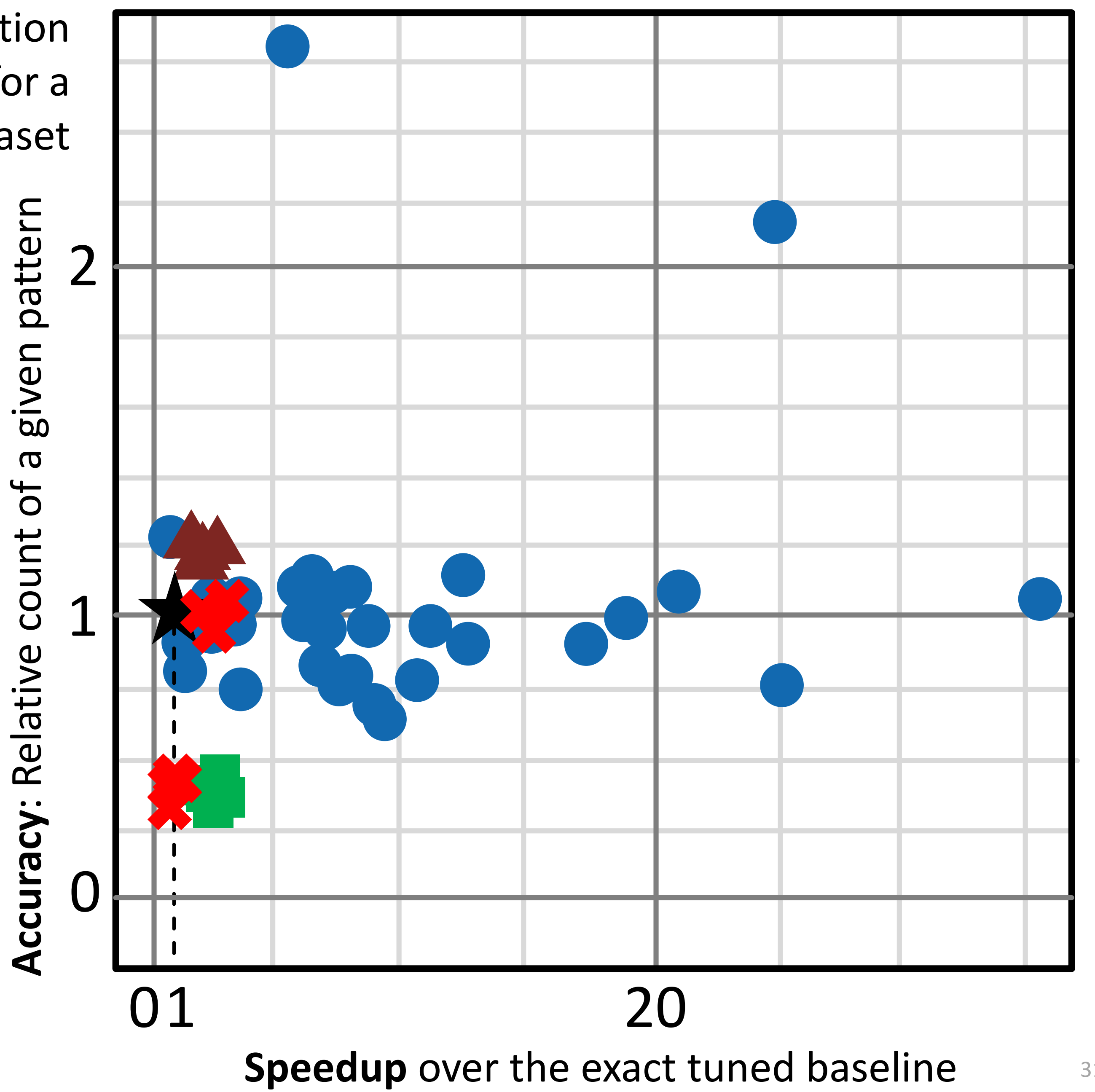
- Heuristics, formal guarantees [3-4]
- Lossy graph compression [5-6]



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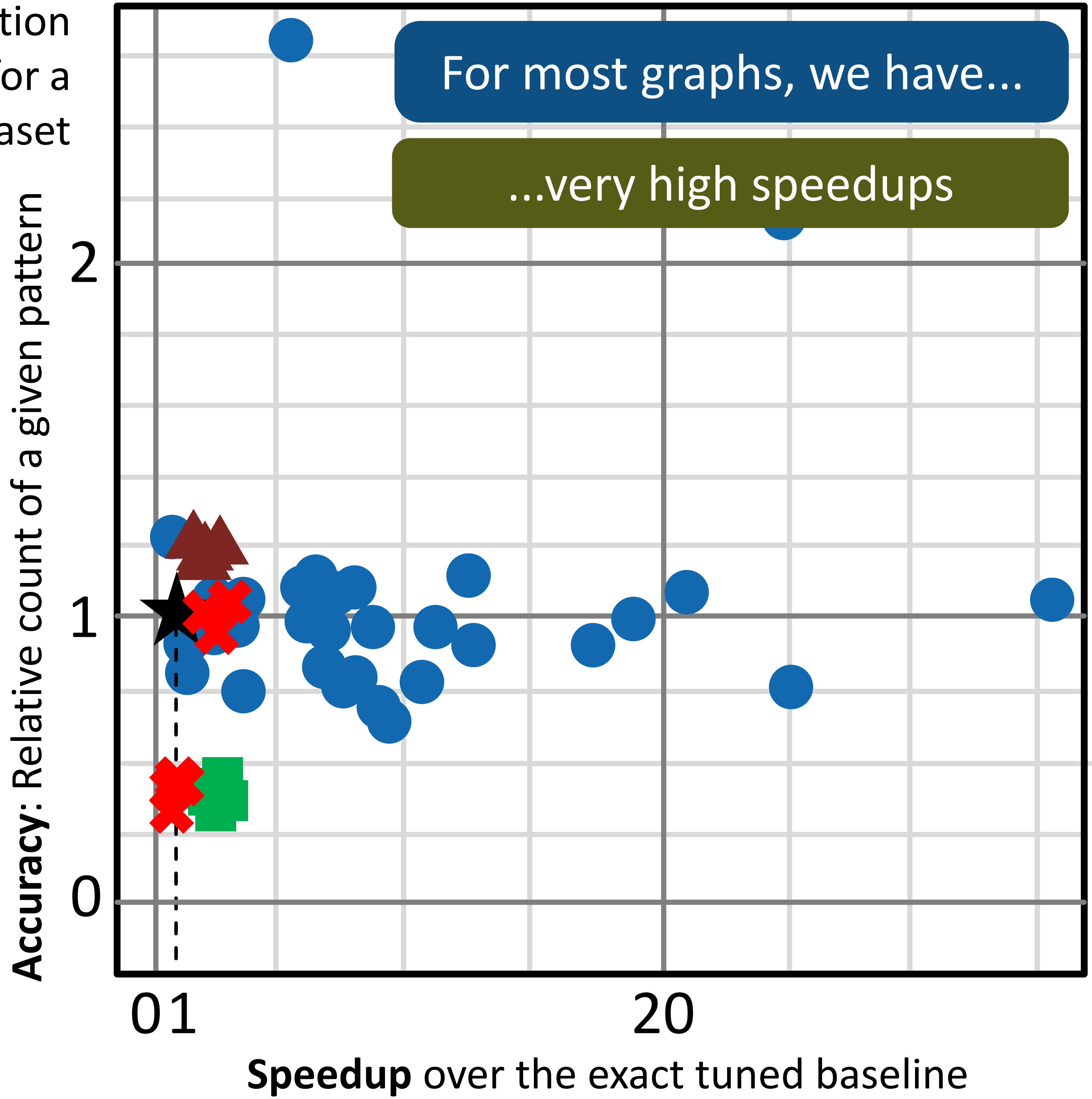

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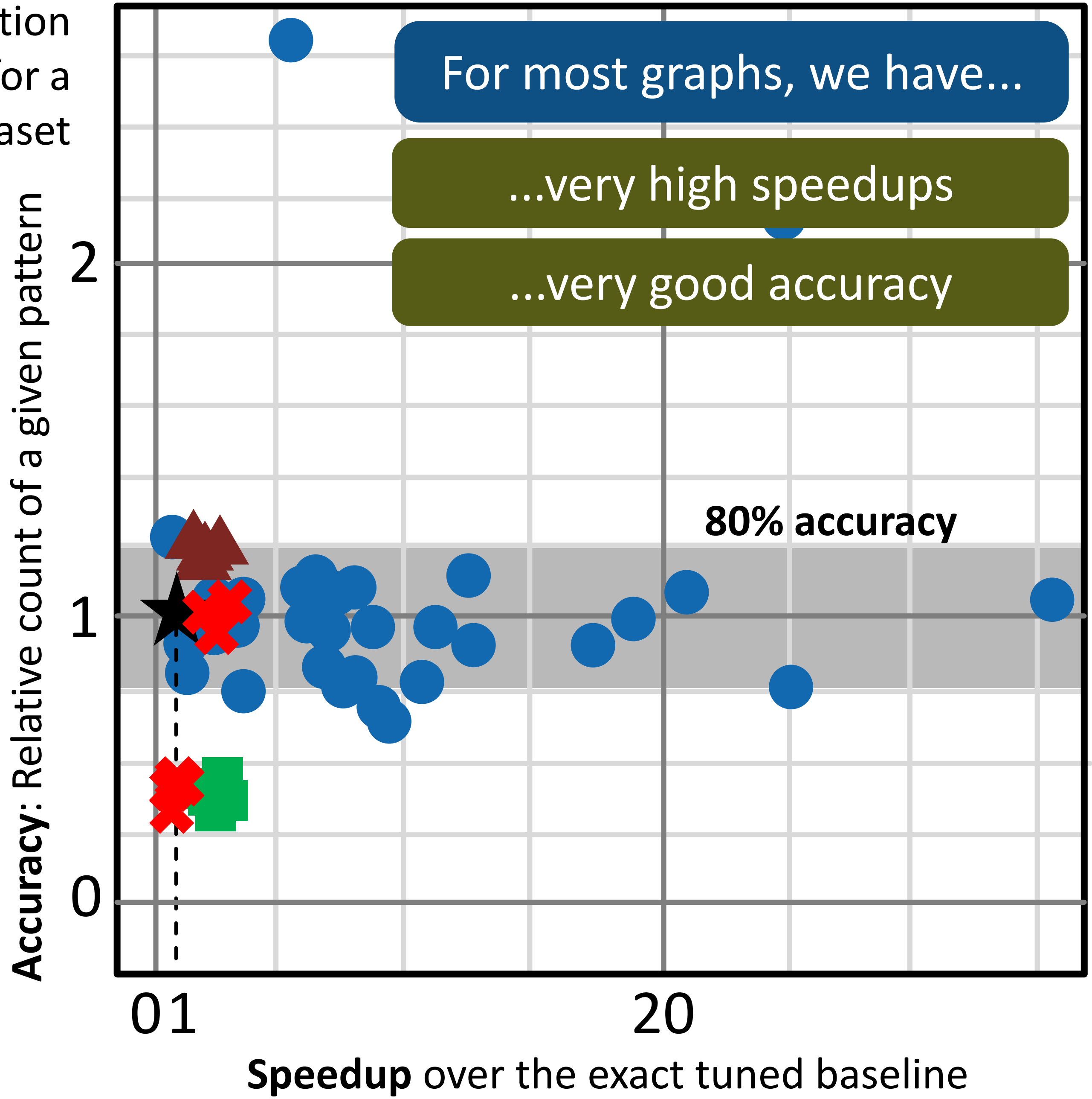

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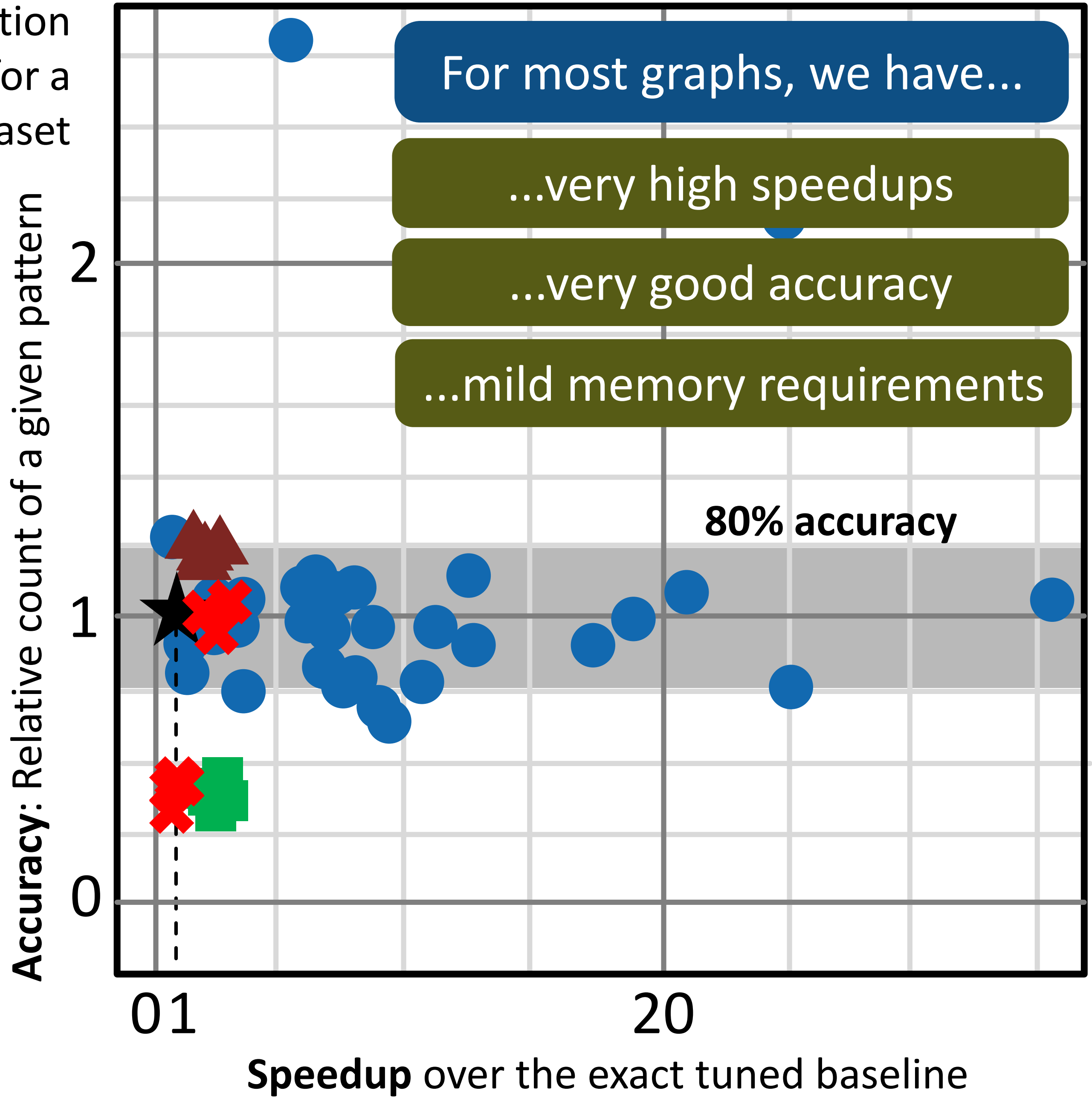

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4-Clique Counting

Cores/threads: 32
Max memory overhead: 20%

Each data point: the execution of a given scheme for a specific graph dataset

★ Exact baseline [1]

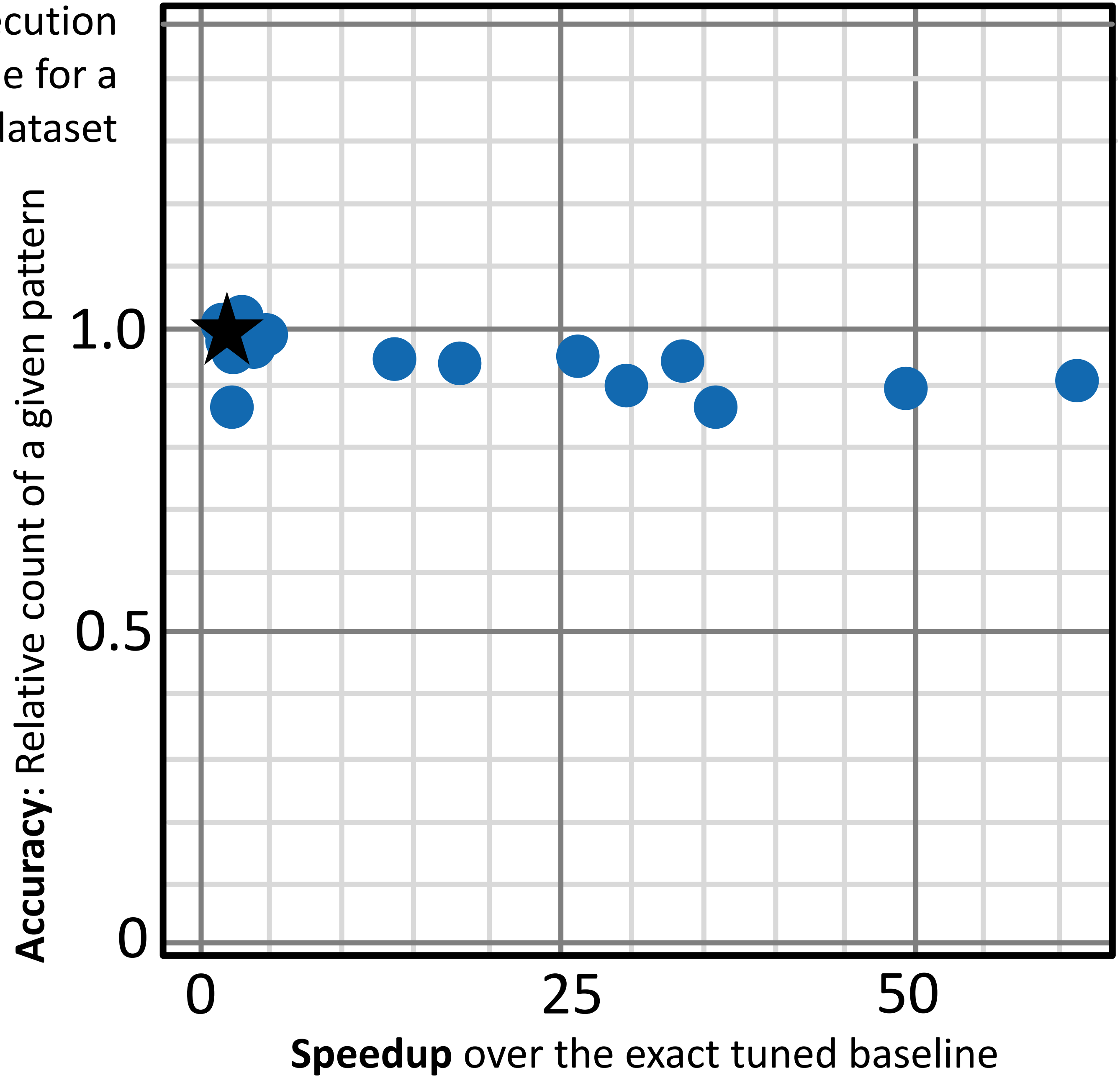
● ProbGraph

For most graphs, we have...

...very high speedups

...very good accuracy

...mild memory requirements



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4-Clique Counting

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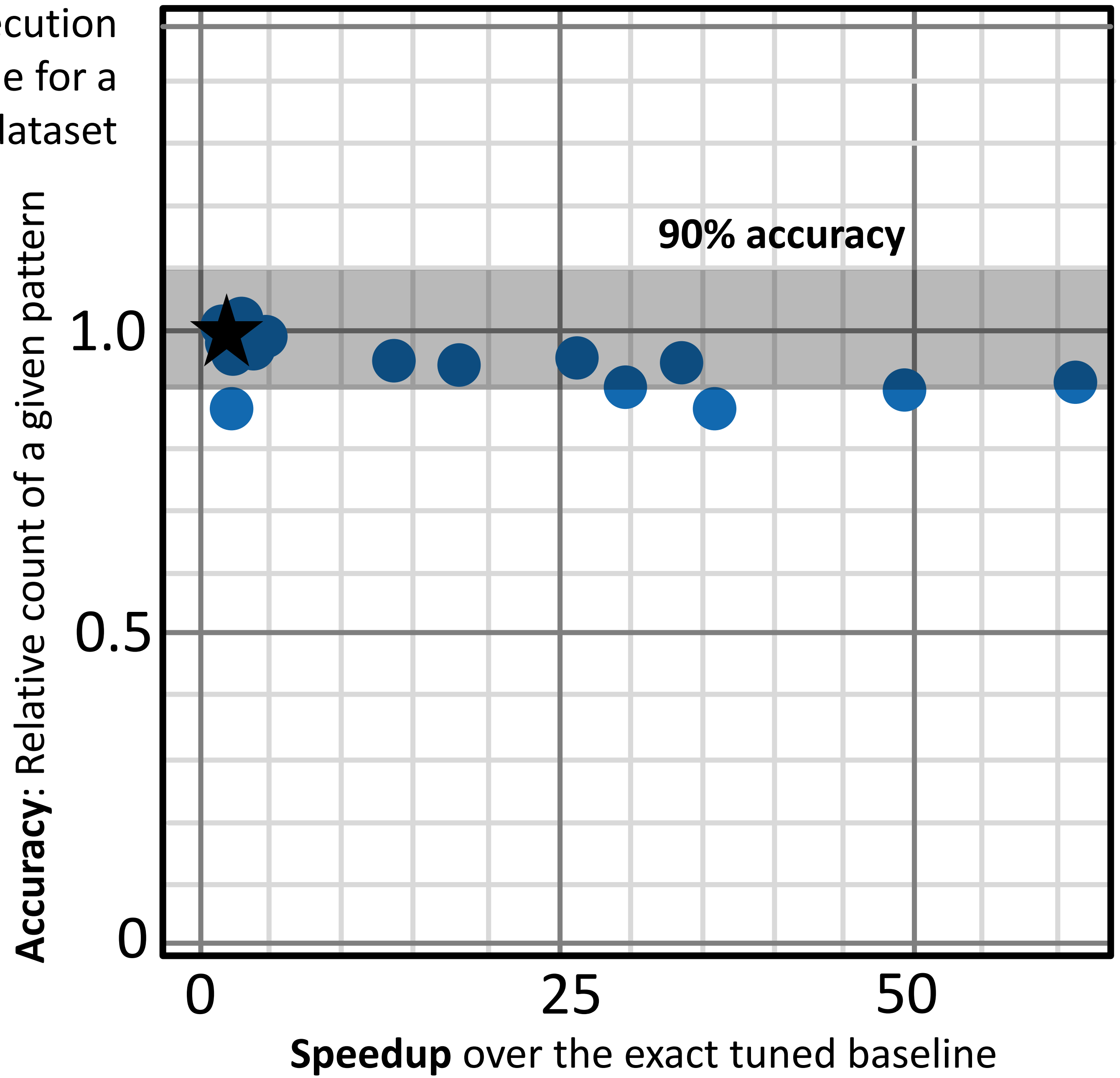

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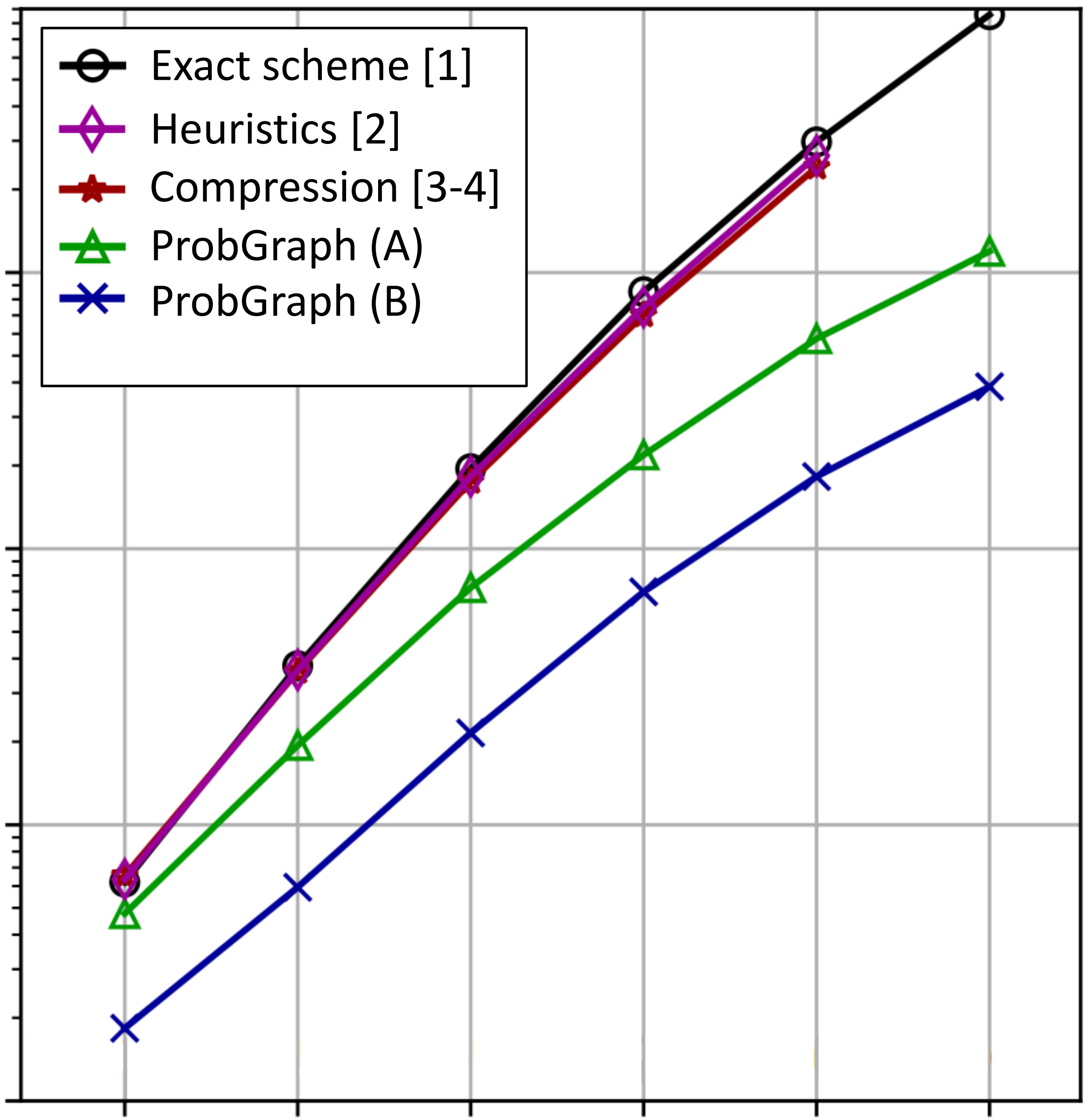
Clustering (Scaling)

Max memory overhead: 20%



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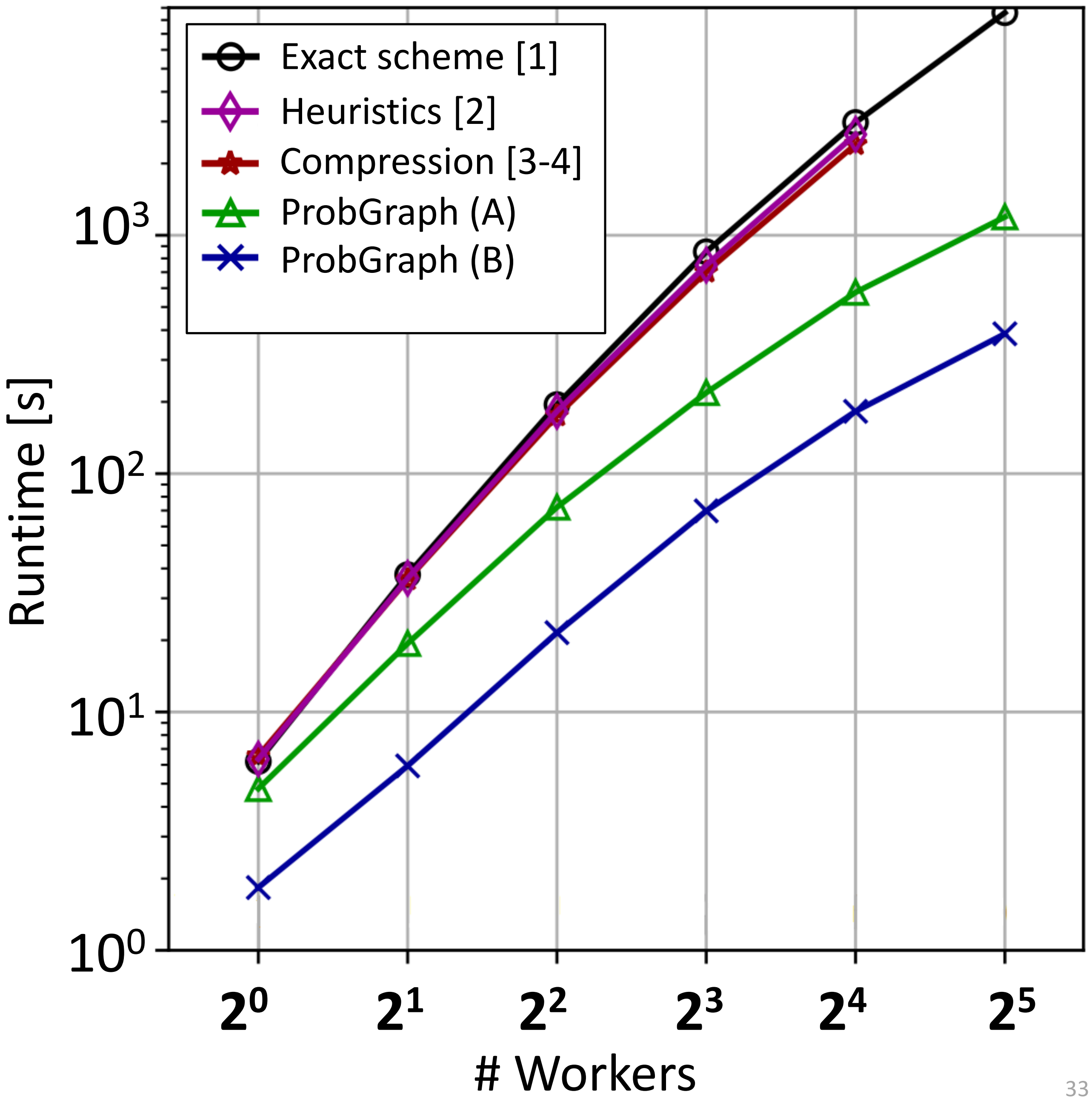

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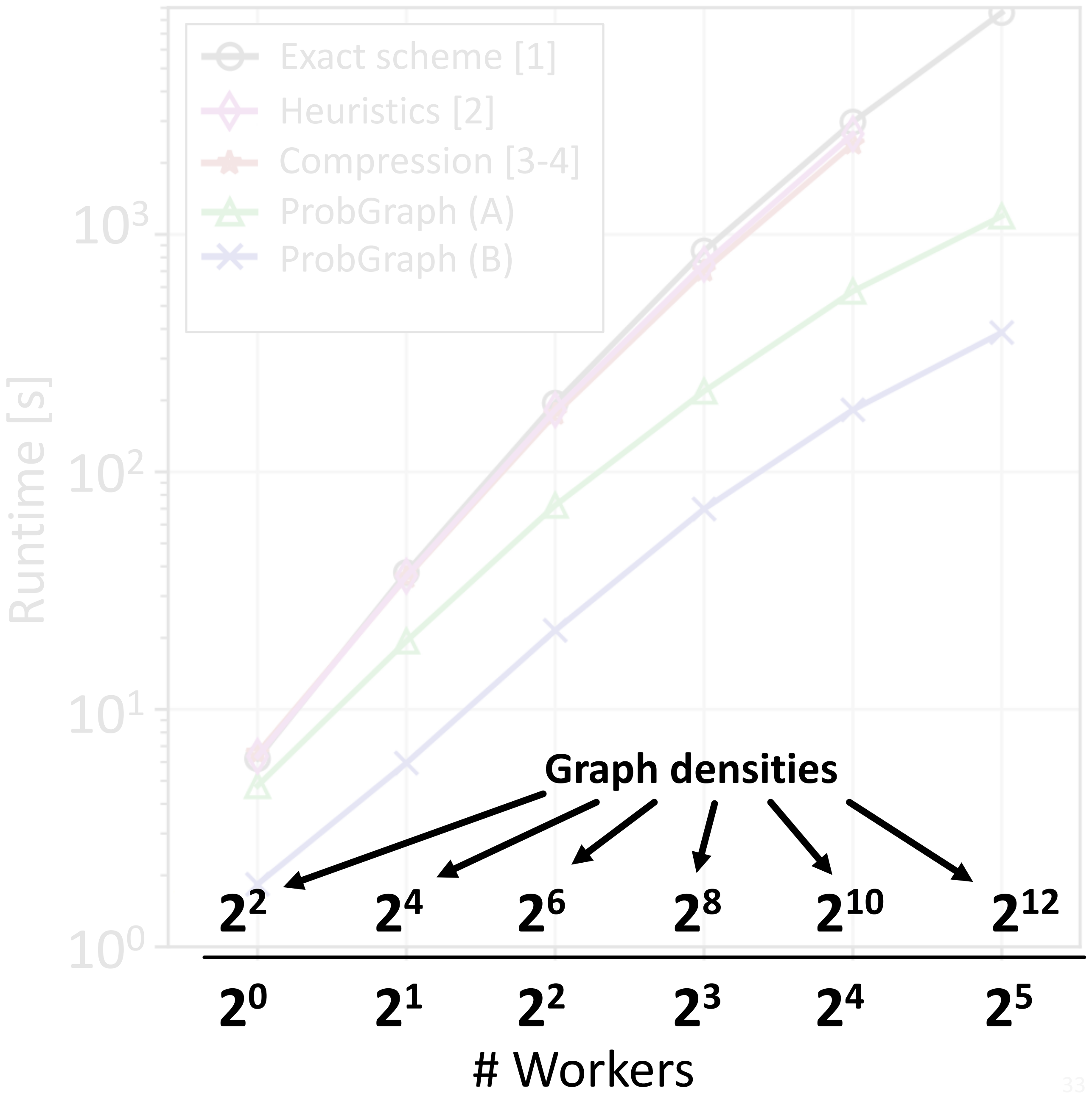

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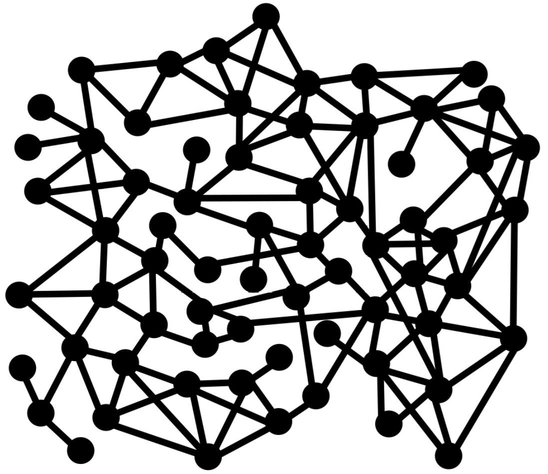

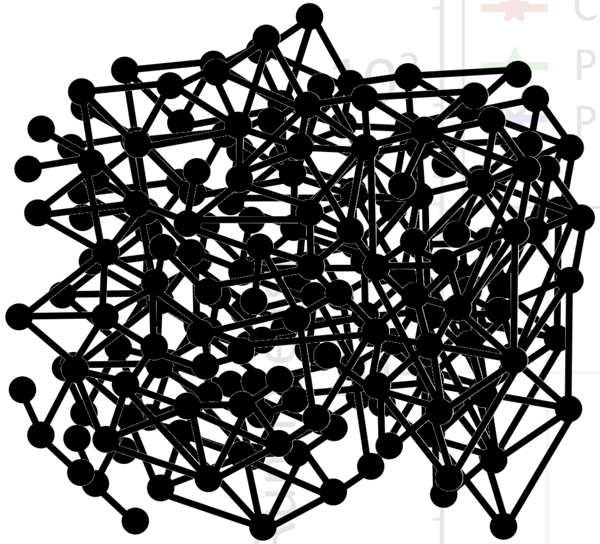

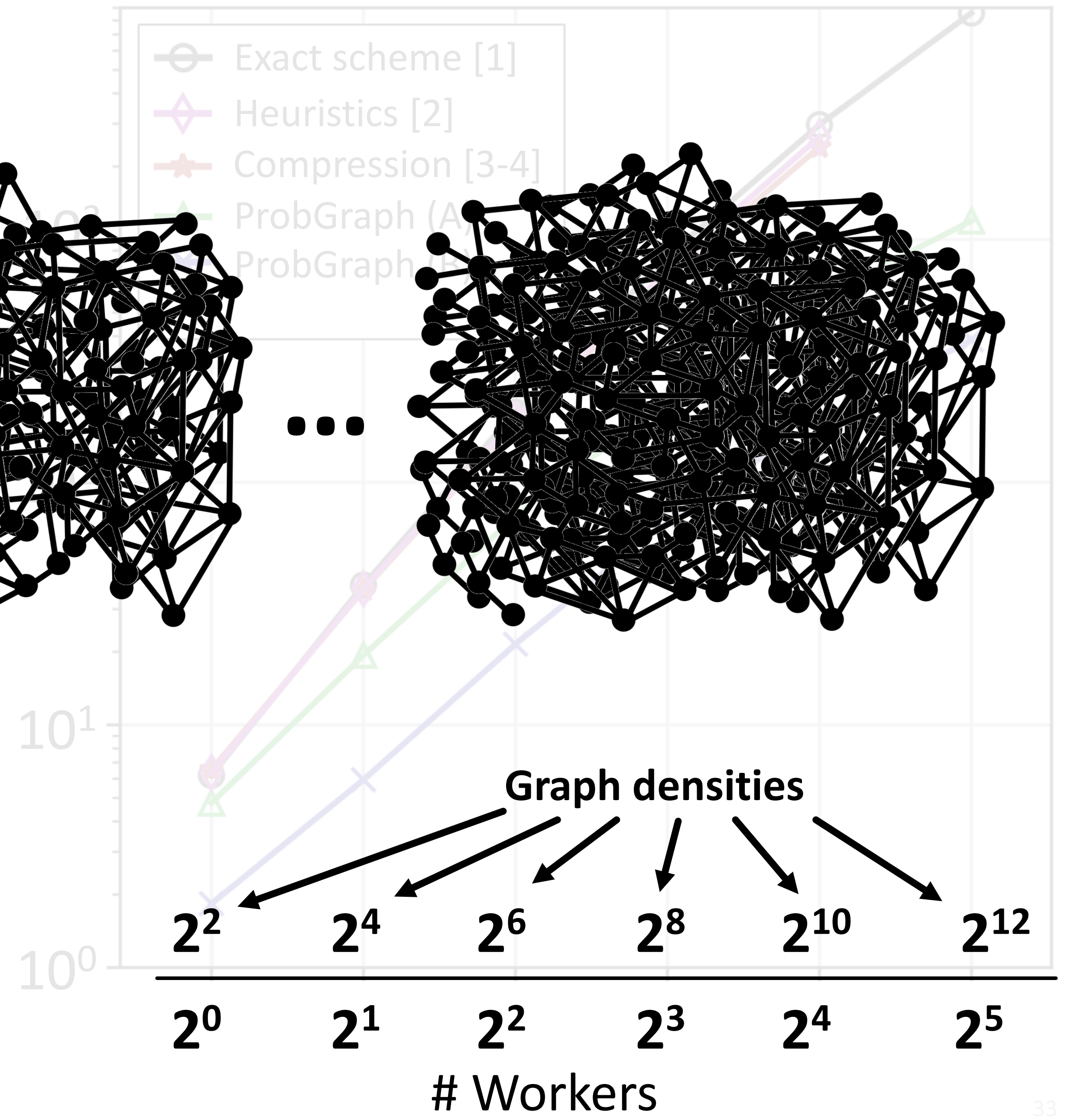

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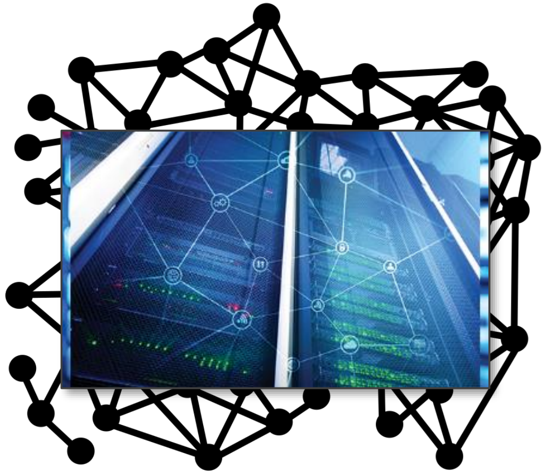

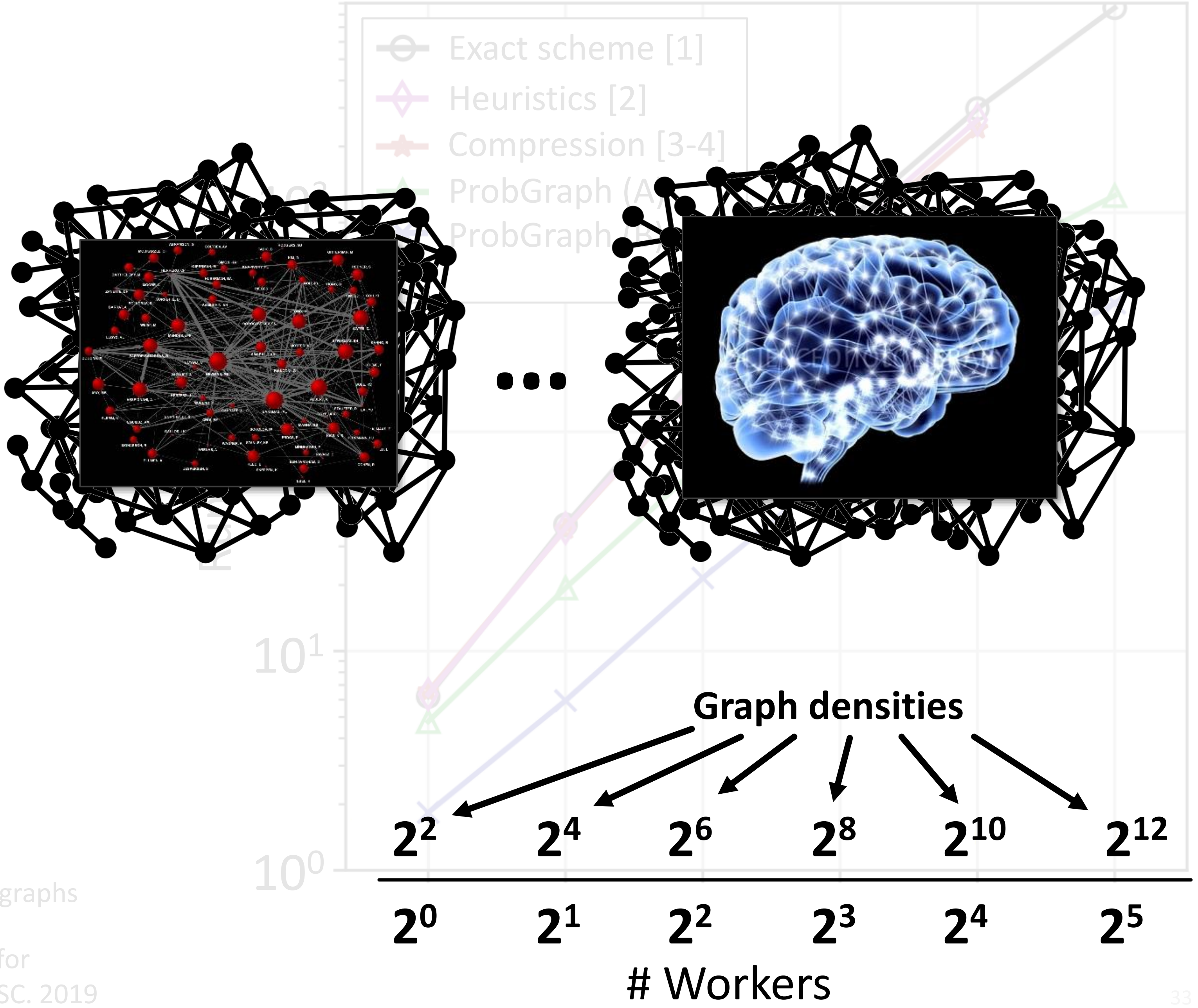

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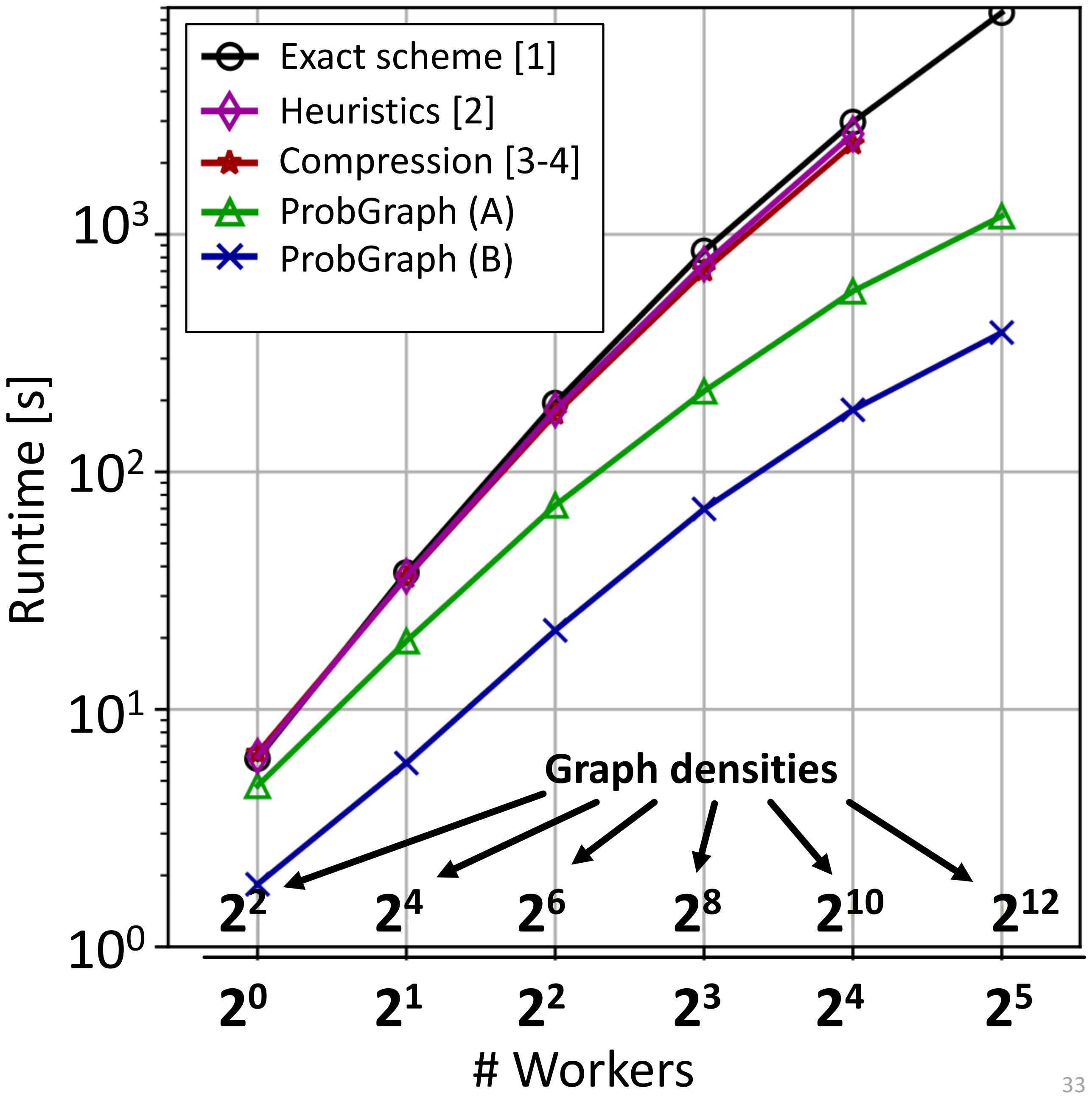

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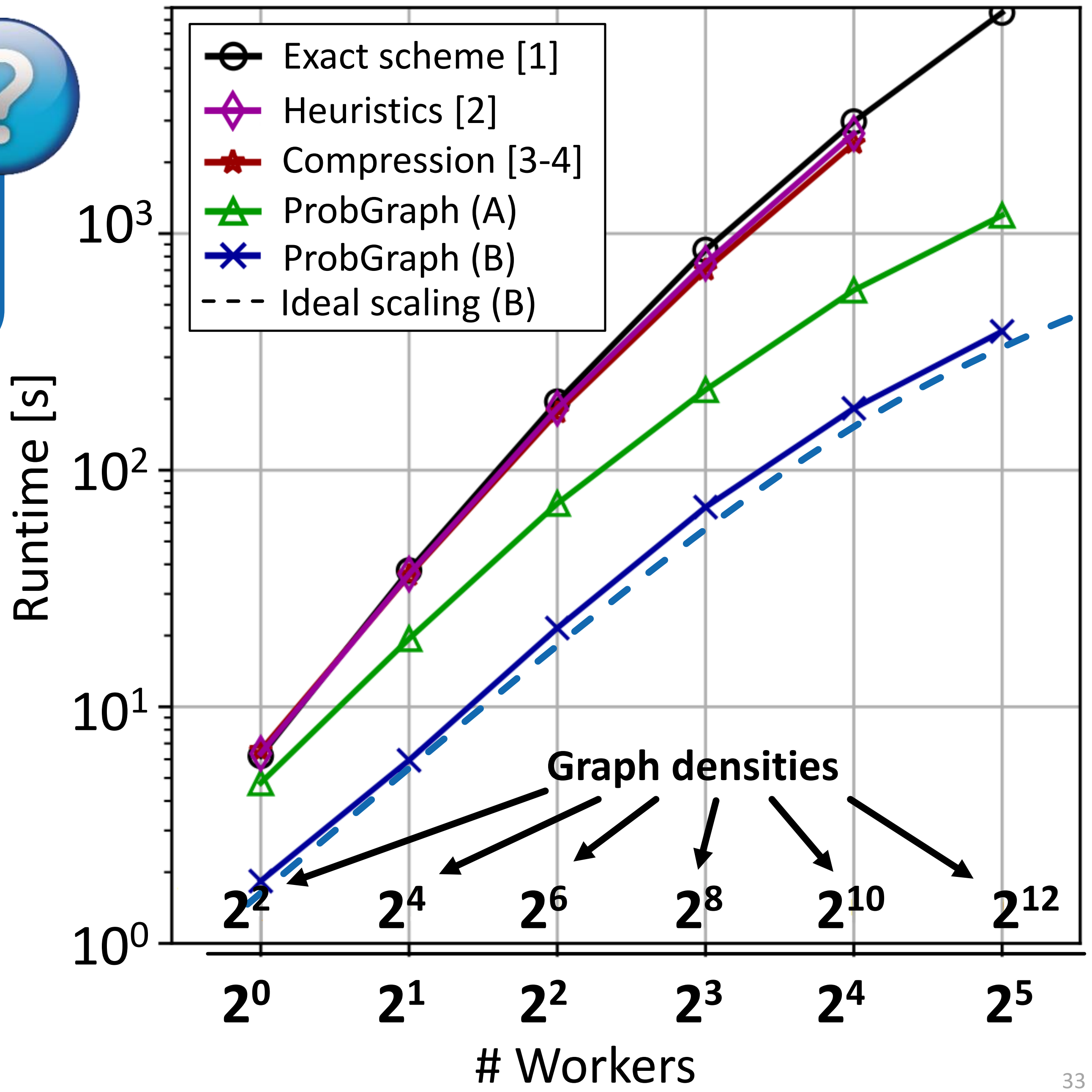
Clustering (Scaling)

Max memory overhead: 20%

Why do we scale so well?



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Clustering (Scaling)

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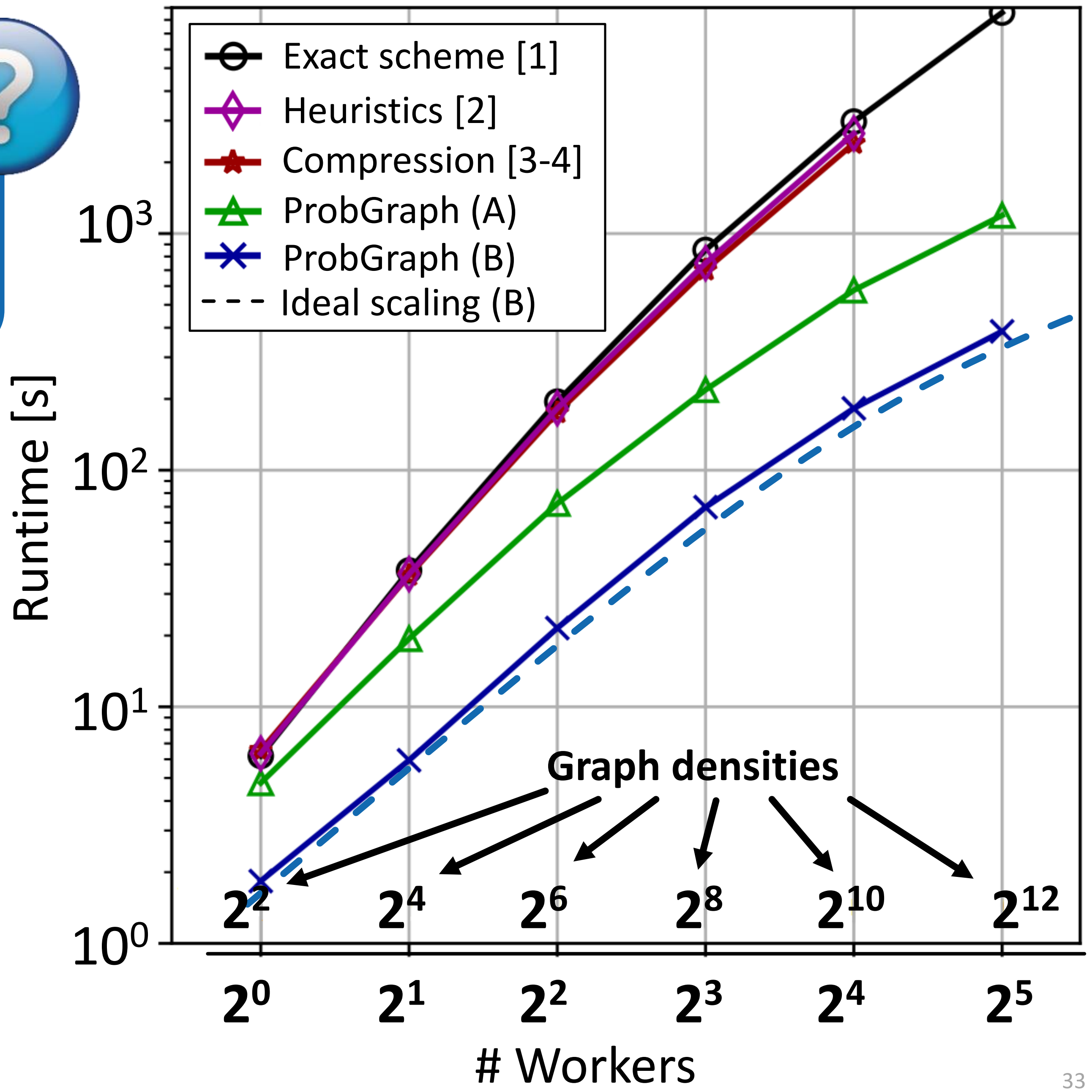
Why do we scale so well?

Great load balancing properties



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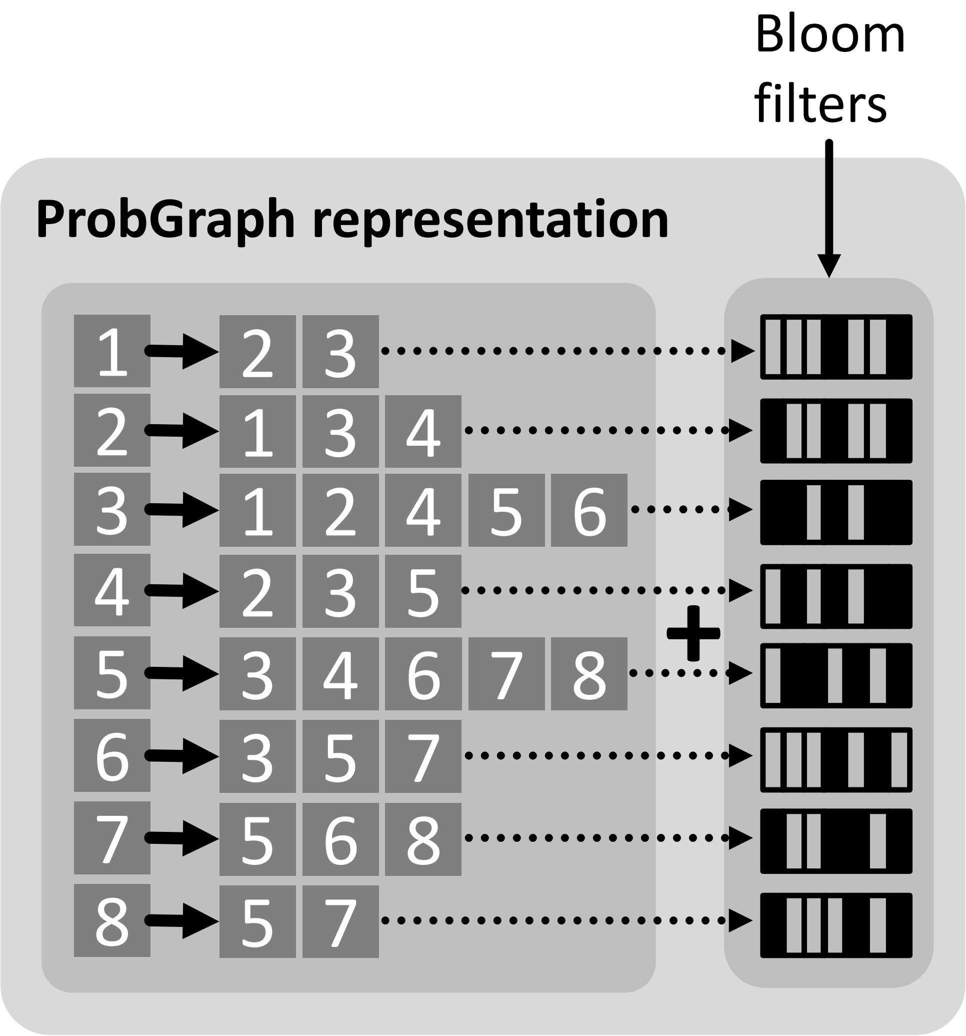
Bloom
filters
ProbGraph representation
1 2 3
2 1 3 4
3 1 2 4 5 6
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5 3 4 6 7 8
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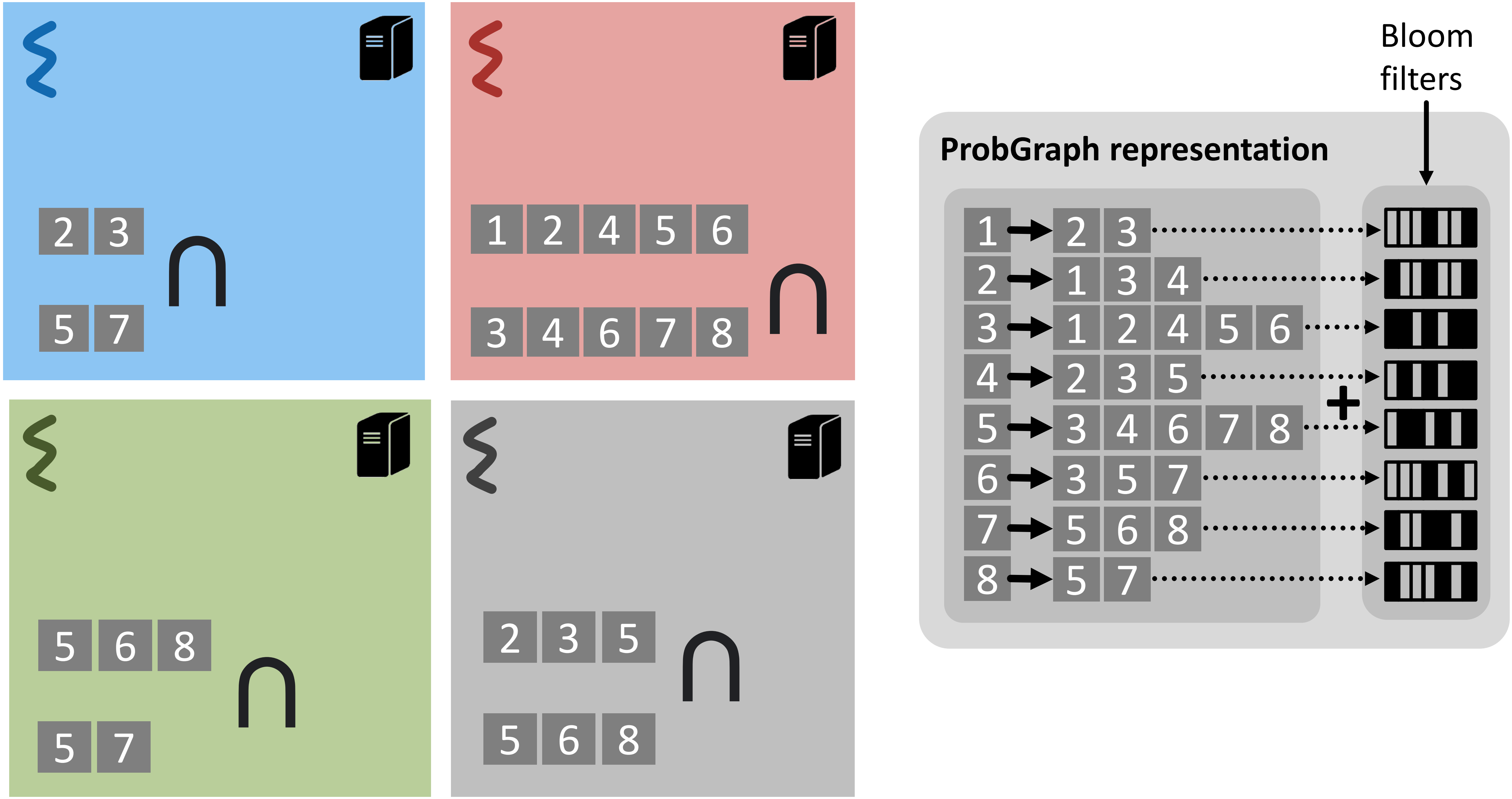
7 5 6 8
8 5 7
+


2 3
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2 3 5
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Bloom filters
ProbGraph representation
1 → 2 3
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5 → 3 4 6 7 8
6 → 3 5 7
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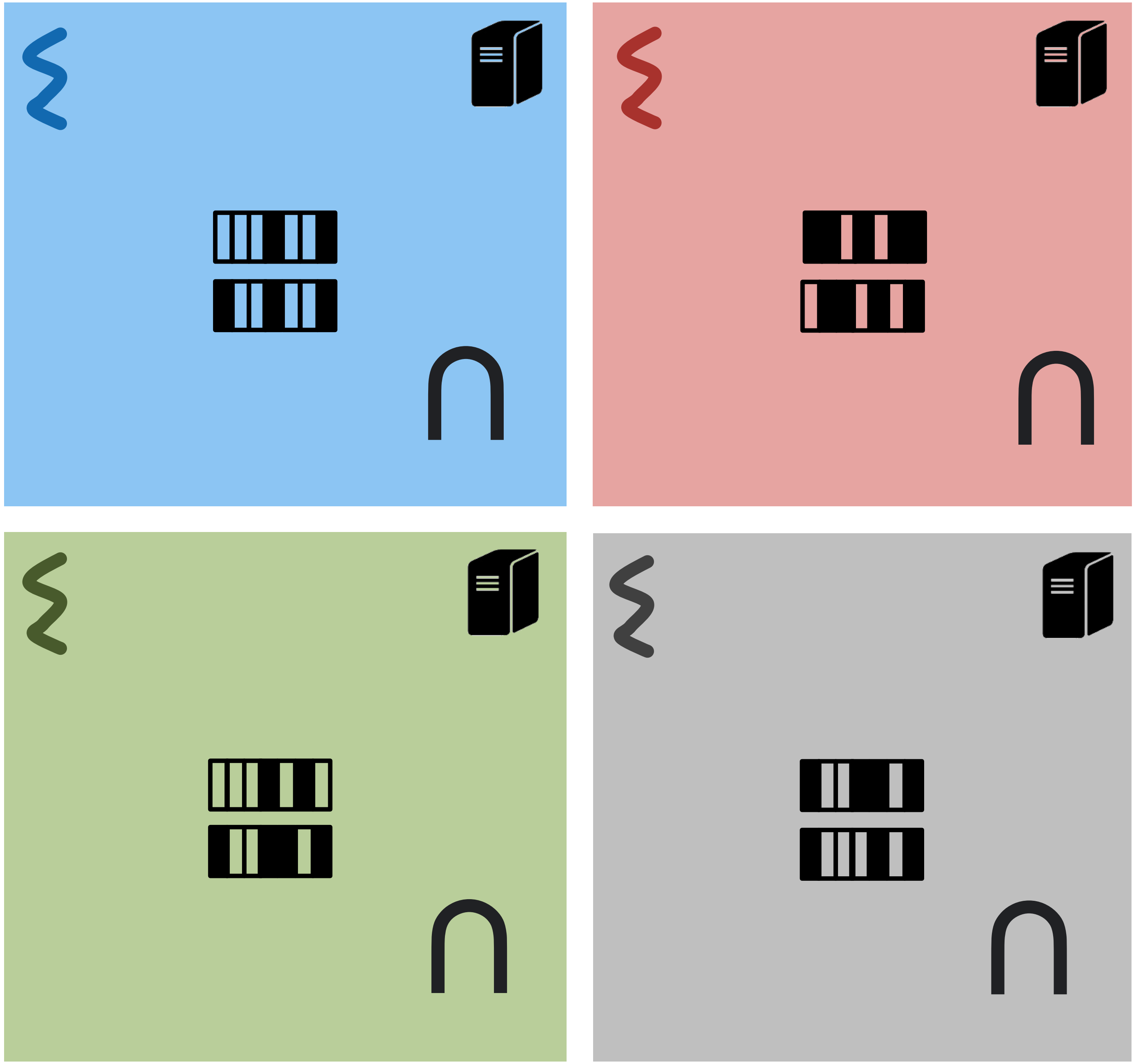

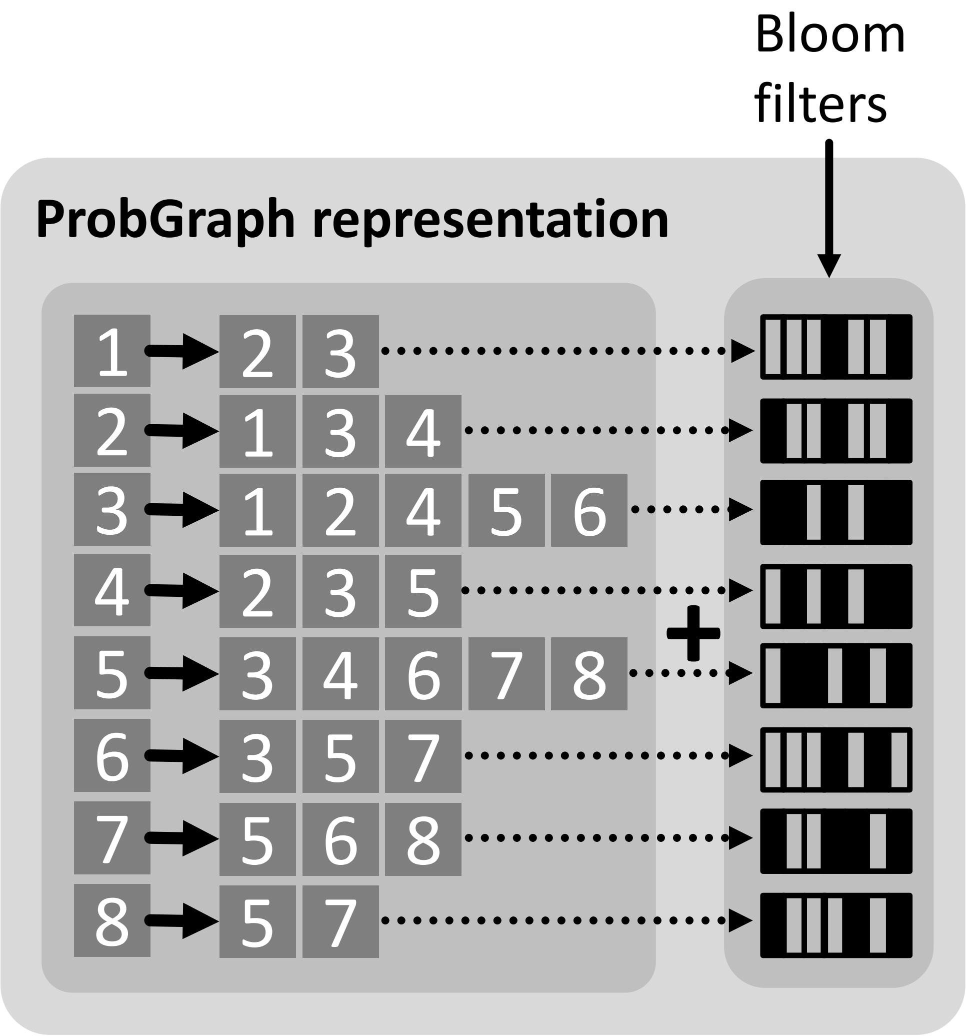
Bloom filters
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1 2 3
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4 2 3 5
5 3 4 6 7 8
6 3 5 7
7 5 6 8
8 5 7
+

...Many more data & a lot of strong theory results!

$$P\left(\left|TC - \widehat{TC}_{1H}\right| \geq t\right) \leq 2\exp\left(-\frac{18\,k\,t^2}{\left(\sum_{v\in V} d(v)^2\right)^2}\right)$$

$$E[(\widehat{|X|} - |X|)^2] \quad (8)$$

$$= E[(\widehat{|X|} - |X|)^2|\mathcal{E}]P(\mathcal{E}) + E[(\widehat{|X|} - |X|)^2|\neg\mathcal{E}]P(\neg\mathcal{E}) \quad (9)$$

$$\leq (1+\varepsilon)E[(\widehat{|X|} - \kappa)^2|\mathcal{E}] + \frac{1+\varepsilon}{\varepsilon}E[(\kappa - |X|)^2|\mathcal{E}] + O(B_X^2 \log^2 B_X)\cdot\exp(-B_X^{\Omega(1)}) \quad (10)$$

$$\leq \frac{(1+\varepsilon)B_X^2}{b^2}E[(\log(B_{X,0}/B_X) - \log(1-1/B_X)^{b|X|})^2|\mathcal{E}] + O((\kappa - |X|)^2) + \exp(-B_X^{\Omega(1)}) \quad (11)$$

$$\leq \frac{(1+\varepsilon)B_X^2}{b^2}E[(\log(B_{X,0}/B_X) - \log(1-1/B_X)^{b|X|})^2|\mathcal{E}] + O(|X|/B_X) \quad (12)$$

$$\leq \frac{(1+\varepsilon)^2B_X^2}{b^2}e^{2b|X|/B_X}E[(B_{X,0}/B_X - (1-1/B_X)^{b|X|})^2|\mathcal{E}] + O(|X|/B_X) \quad (13)$$

$$\leq \frac{(1+\varepsilon)^2B_X^2}{b^2}e^{2b|X|/(B_X-1)}\cdot E[(B_{X,0}/B_X - (1-1/B_X)^{b|X|})^2]/P[\mathcal{E}] + O(|X|/B_X) \quad (14)$$

$$= ((1+\varepsilon)^2 + o(1))\frac{B_X^2}{b^2}e^{2b|X|/(B_X-1)}\cdot E[(B_{X,0}/B_X - (1-1/B_X)^{b|X|})^2] + O(|X|/B_X) \quad (15)$$

$$= ((1+\varepsilon)^2 + o(1))\frac{e^{2b|X|/(B_X-1)}}{b^2}Var[B_{X,0}] + O(|X|/B_X) \quad (16)$$

$$\leq ((1+\varepsilon)^2 + o(1))e^{2b|X|/(B_X-1)}\cdot\left(e^{-\frac{b|X|}{B_X}}\frac{B_X}{b^2} - B_X/b^2 - |X|/b\right) + O(|X|/B_X) \quad (17)$$

$$\leq ((1+\varepsilon)^2 + o(1))\left(e^{|X|b/(B_X-1)}\frac{B_X}{b^2} - B_X/b^2 - |X|/b\right) + O(|X|/B_X) \quad (18)$$

$$\leq ((1+\varepsilon)^2 + o(1))\left(e^{|X|b/(B_X-1)}\frac{B_X}{b^2} - B_X/b^2 - |X|/b\right) \quad (19)$$

Reference	Constr. time	Memory used
Doulion [46]	$O(m)$	$O(pm)$
Colorful [47]	$O(m)$	$O(pm)$
Sketching [48]	$O(km)$	$O(kn)$
ASAP [49]	n/a	$O(n+m)$
GAP [50]	$O(m)\dagger$	$O(m')\dagger$
Slim Gr. [51]	$O(m)$	$O(pm)$
Eden et al. [52]	n/a	$O\left(\frac{n}{TC^{1/3}}\right)$
Assadi et al. [53]	n/a	$O(1)$
Tětek [54]	n/a	$\left(\frac{m^{1.41}}{TC^{0.82}}\right)$
$\widehat{TC}_{AND}$ (BF)	$O(bm)$	$O(n+m)$
$\widehat{TC}_{kH}$ (MH)	$O(km)$	$O(n+m)$
$\widehat{TC}_{1H}$ (MH)	$O(km)$	$O(n+m)$

Theorem A.6. *Let* $Y_1 = \ldots$ *and assume we partition* ... $\mathcal{X}_1, \cdots, \mathcal{X}_X$ *such that estim*... *independent. Then for any* ... $S = \sum_{i=1}^{n} C_i \frac{J}{1+J}$

$P(|Y_1 - S| > t), P(|Y_k - S| > \ldots$

CSR (merge)

Work: $O(d_u + d_v)$

Depth: $O(\log(d_u + d_v \ldots$

(work)	(depth)
$O(bd_v)$	$O(\log(bd_v))$
$O(kd_v)$	$O(\log d_v)$

PG (BF)	PG (MH)
$\frac{ndB_X}{W}\big)$	$O(ndk)$
$\log\left(\frac{B_X}{W}\right)\big)$	$O(\log k)$
$\frac{nd^2B_X}{W}\big)$	$O(nd^2k)$
$\log d \log\left(\frac{B_X}{W}\right)\big)$	$O(\log^2 k)$

Approximate Graph Processing: Our Objectives

- Little parallelism → Rich parallelism ✓
- Specific → Wide applicability ✓
- No/loose accuracy guarantees → Strong accuracy guarantees ✓
- Slow → High performance
- Low accuracy → High accuracy
- Large memory overheads → Low & controllable memory overheads

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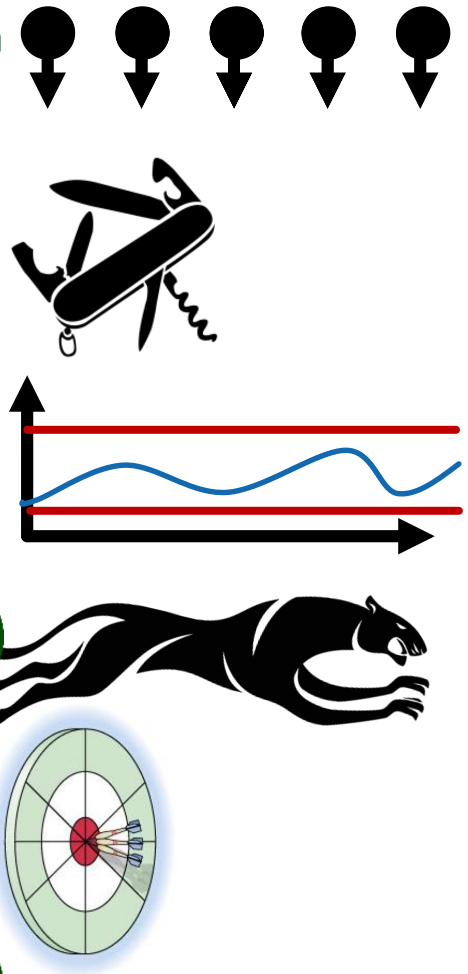
Conclusion: ProbGraph Enables Approximate Graph Mining with...

- Rich parallelism
- Wide applicability
- Strong accuracy guarantees
- High performance
- High accuracy
- Low & controllable memory overheads



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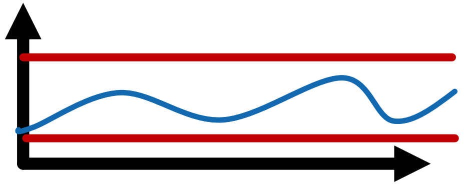
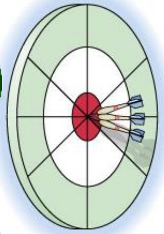


- High performance

- High accuracy



- Low & controllable memory overheads

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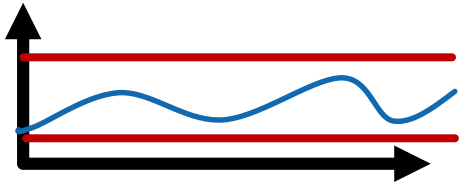

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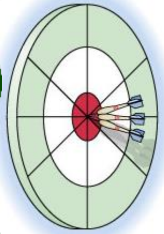

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Thank you

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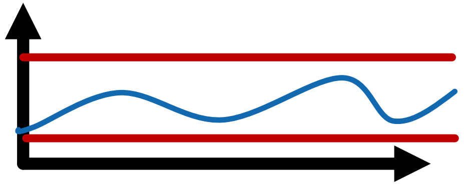

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Thank you

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- spcl.inf.ethz.ch
- github.com/spcl

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