ASAP: Fast, Approximate Graph Pattern Mining at Scale

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[*]UC Berkeley [◆]Johns Hopkins University [+]University of Wisconsin & Microsoft

OSDI, October 10, 2018

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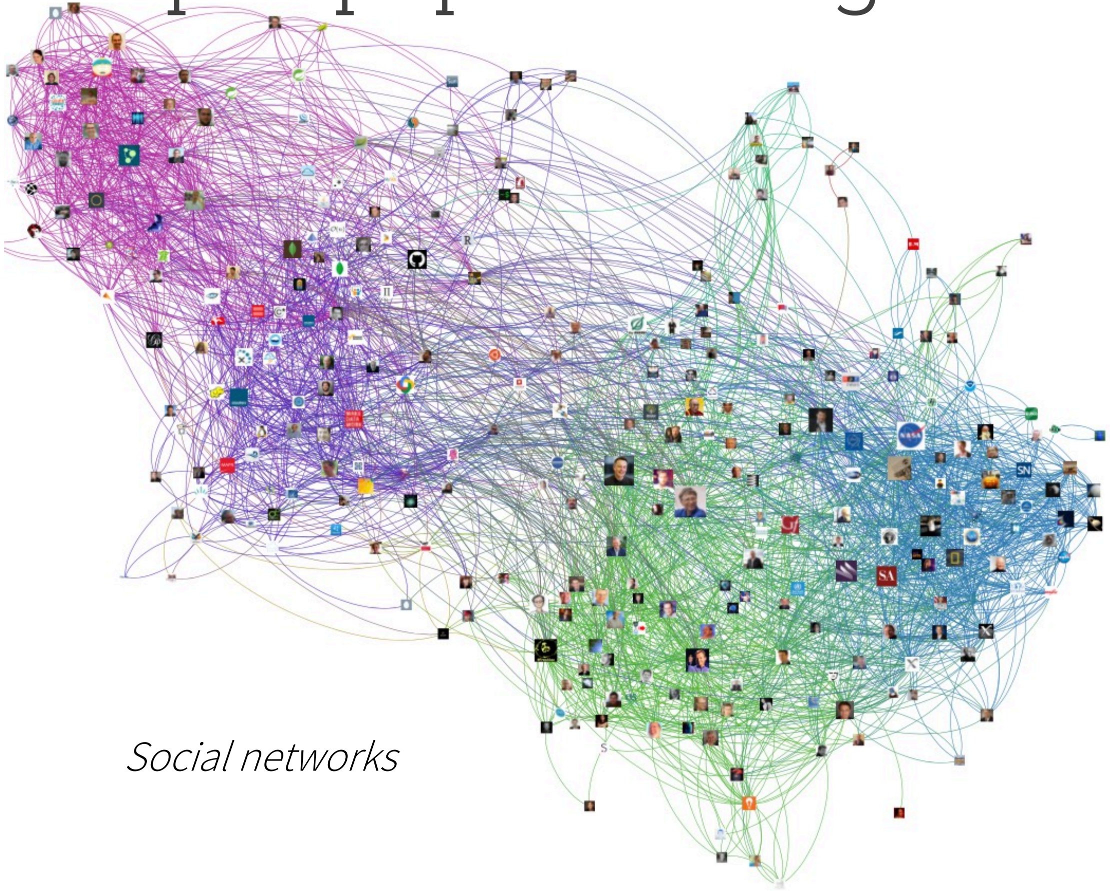
Graphs popular in big data analytics



Social networks

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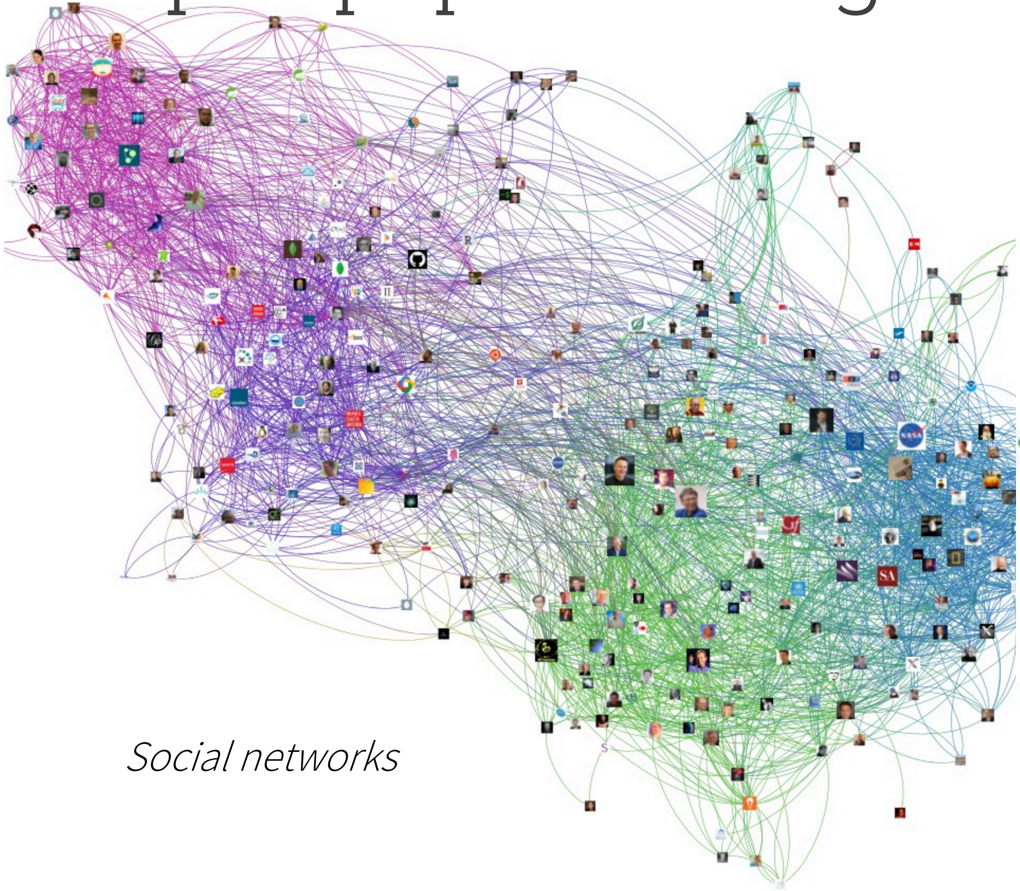

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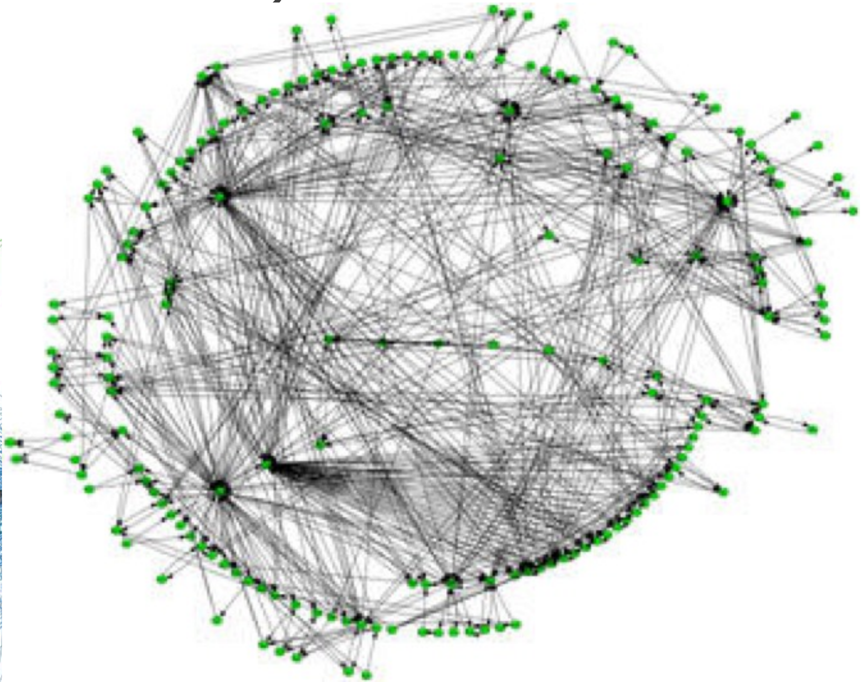

Metabolic network of a single cell organism

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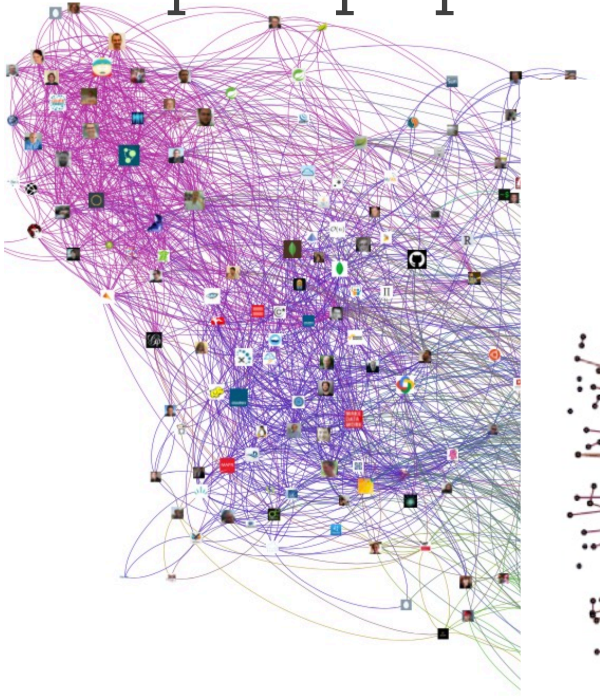

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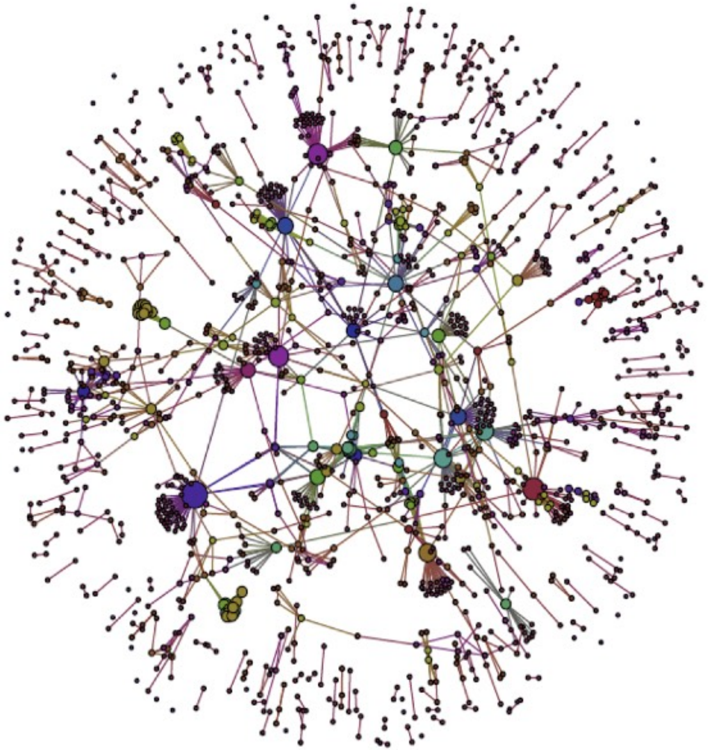
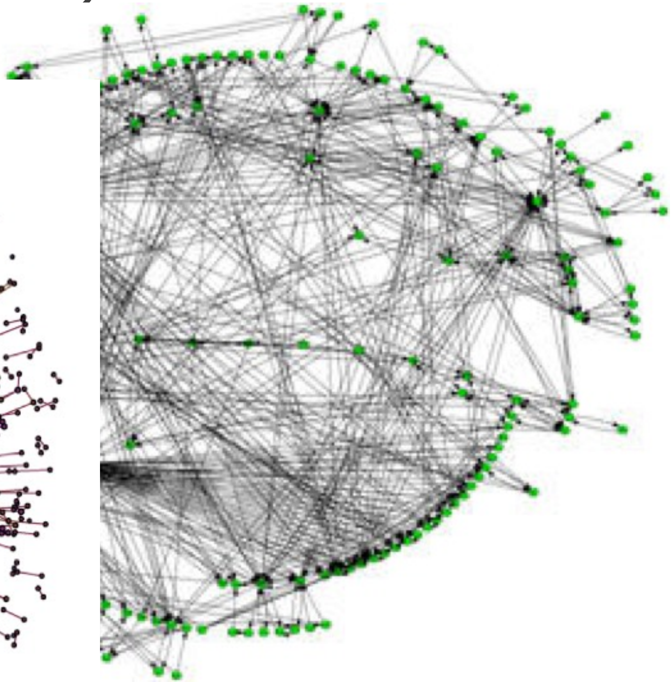


Tuberculosis



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Also popular in traditional enterprises*

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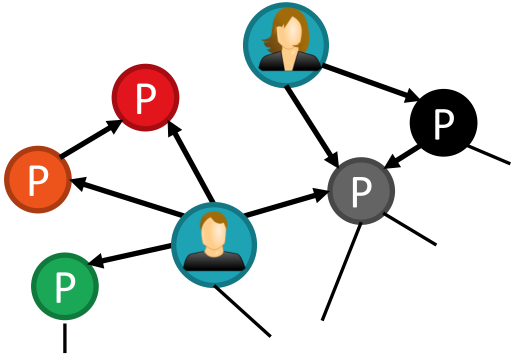

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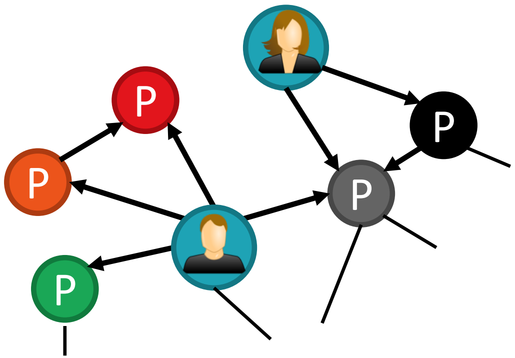
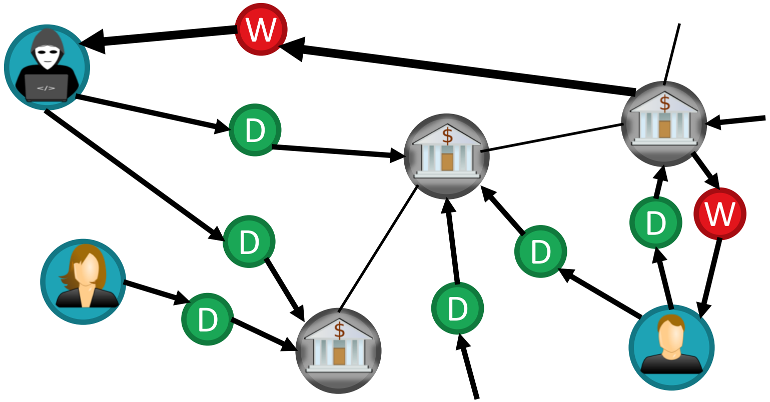


Products and customers

Transactions and involved entities



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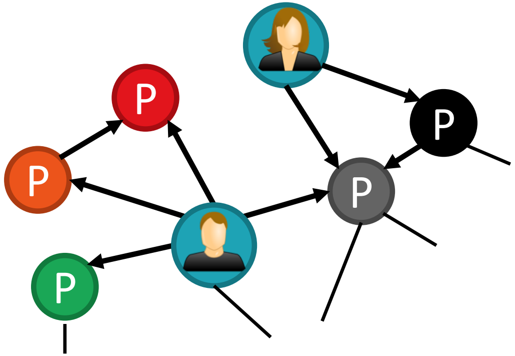

Which (classes of) products are frequently bought together?

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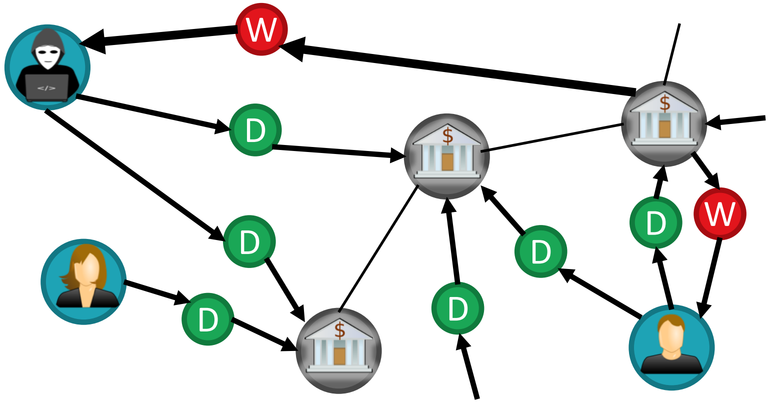

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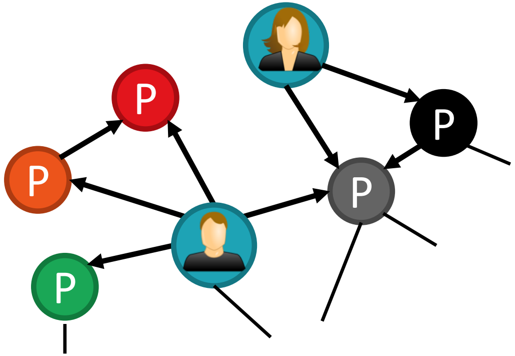

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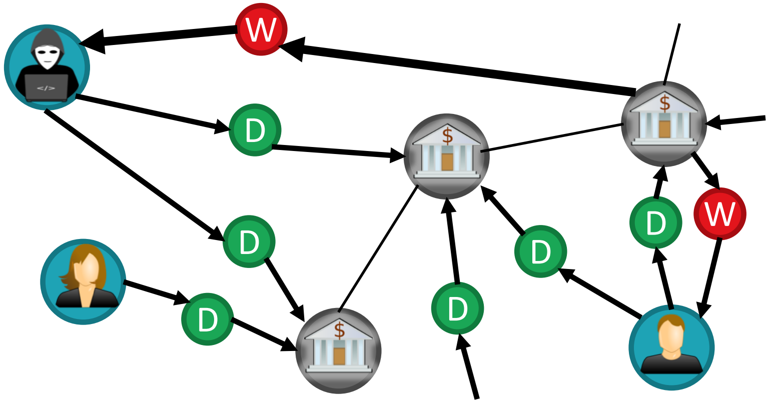
Small deposits followed by large withdrawal



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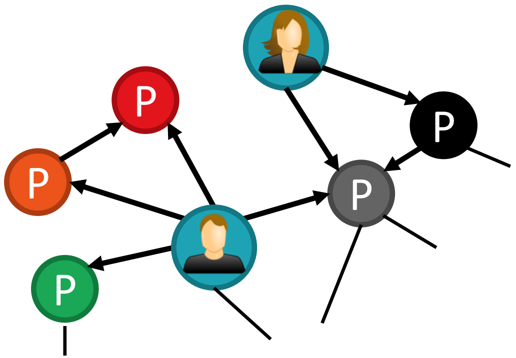

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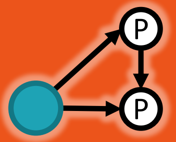

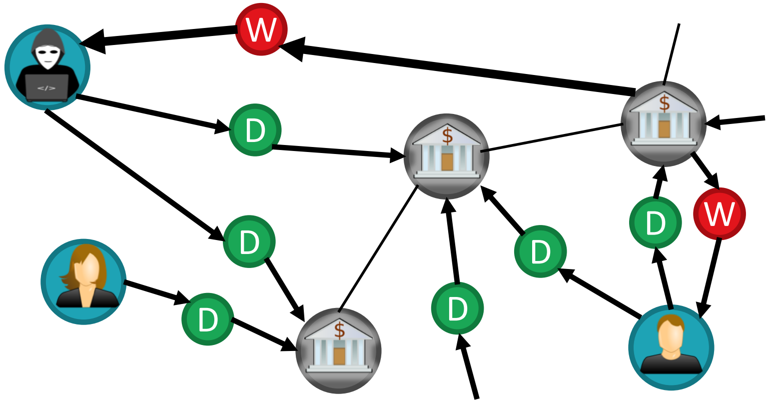

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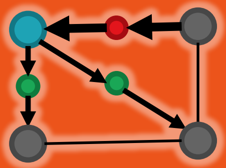

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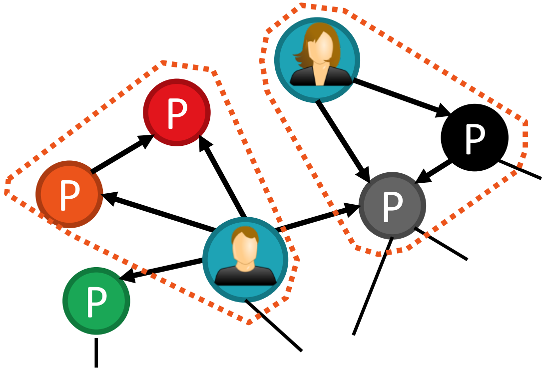

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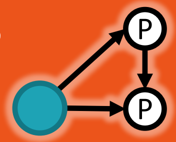

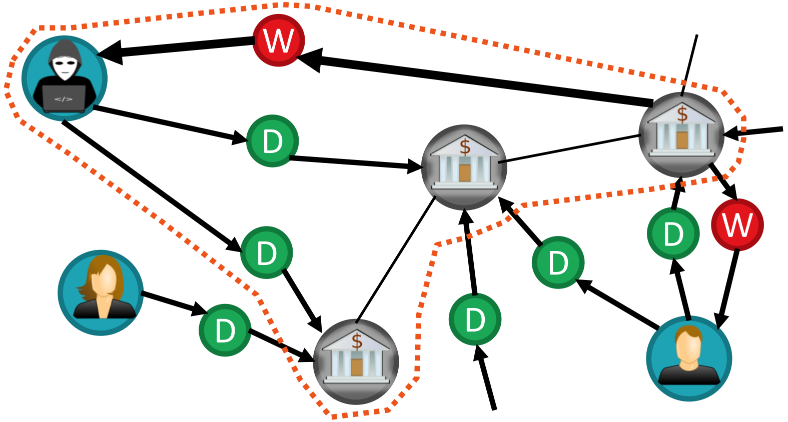

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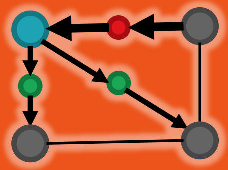

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Discover structural patterns in the underlying graph

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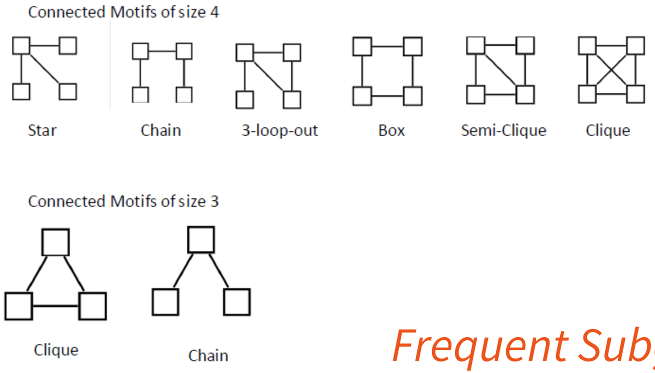
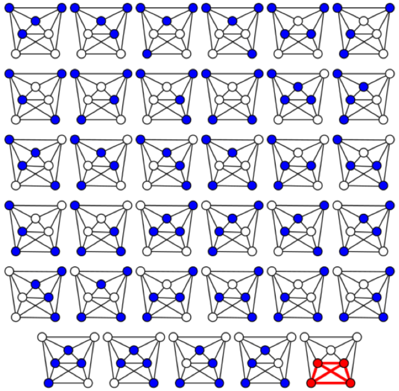


Motifs

Frequent Subgraphs



Cliques

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Standard approach: Iterative expansion

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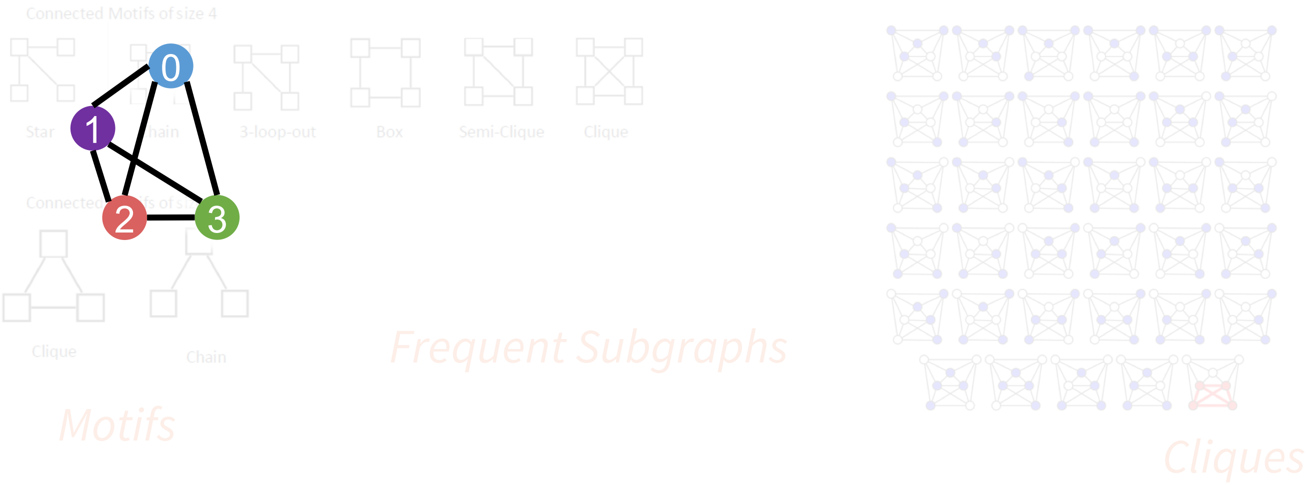

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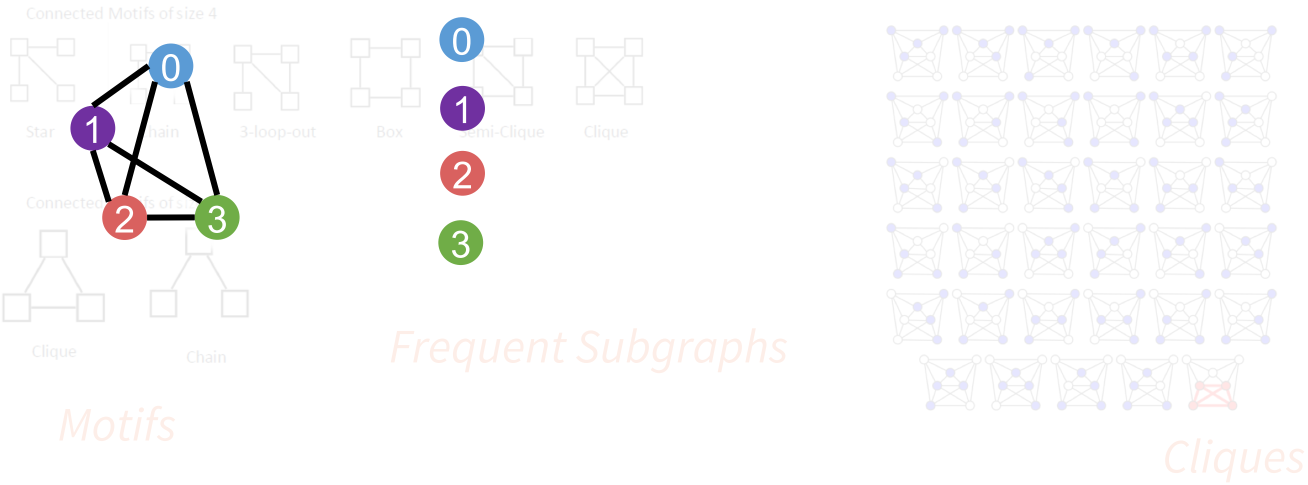

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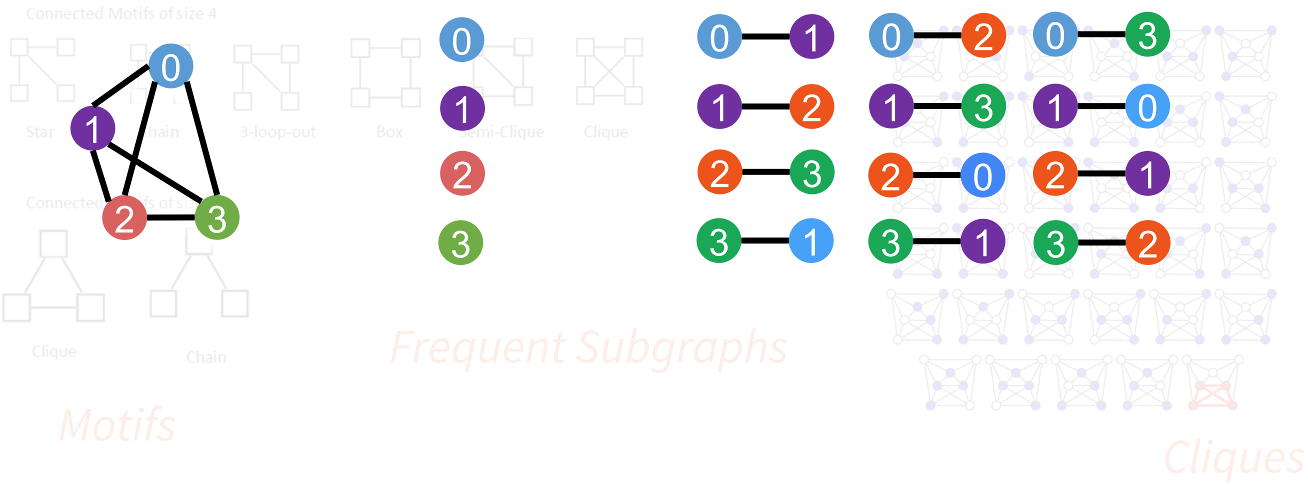

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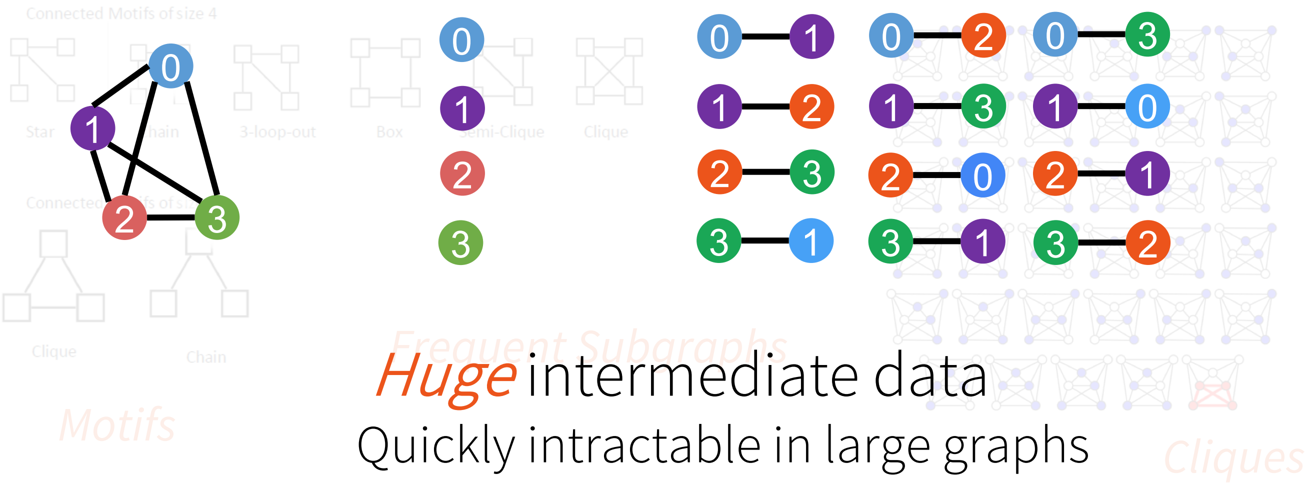

Huge intermediate data

Quickly intractable in large graphs

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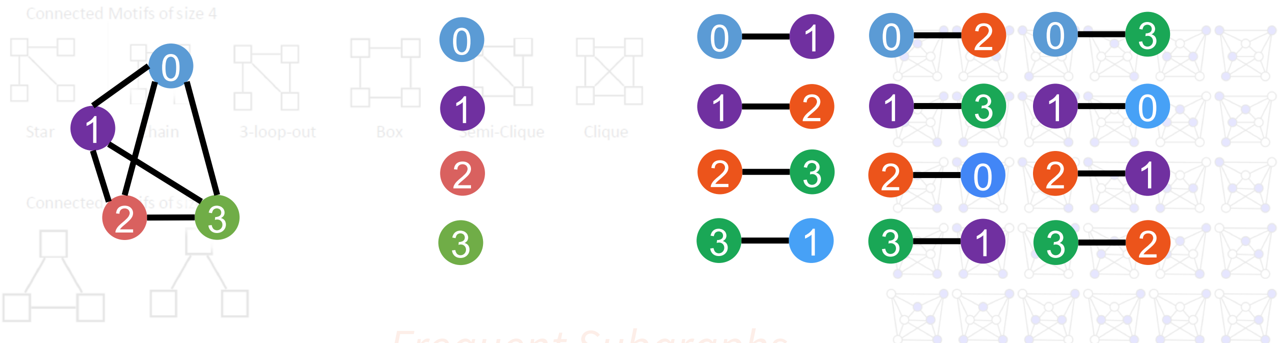

Challenging to mine patterns in large graphs

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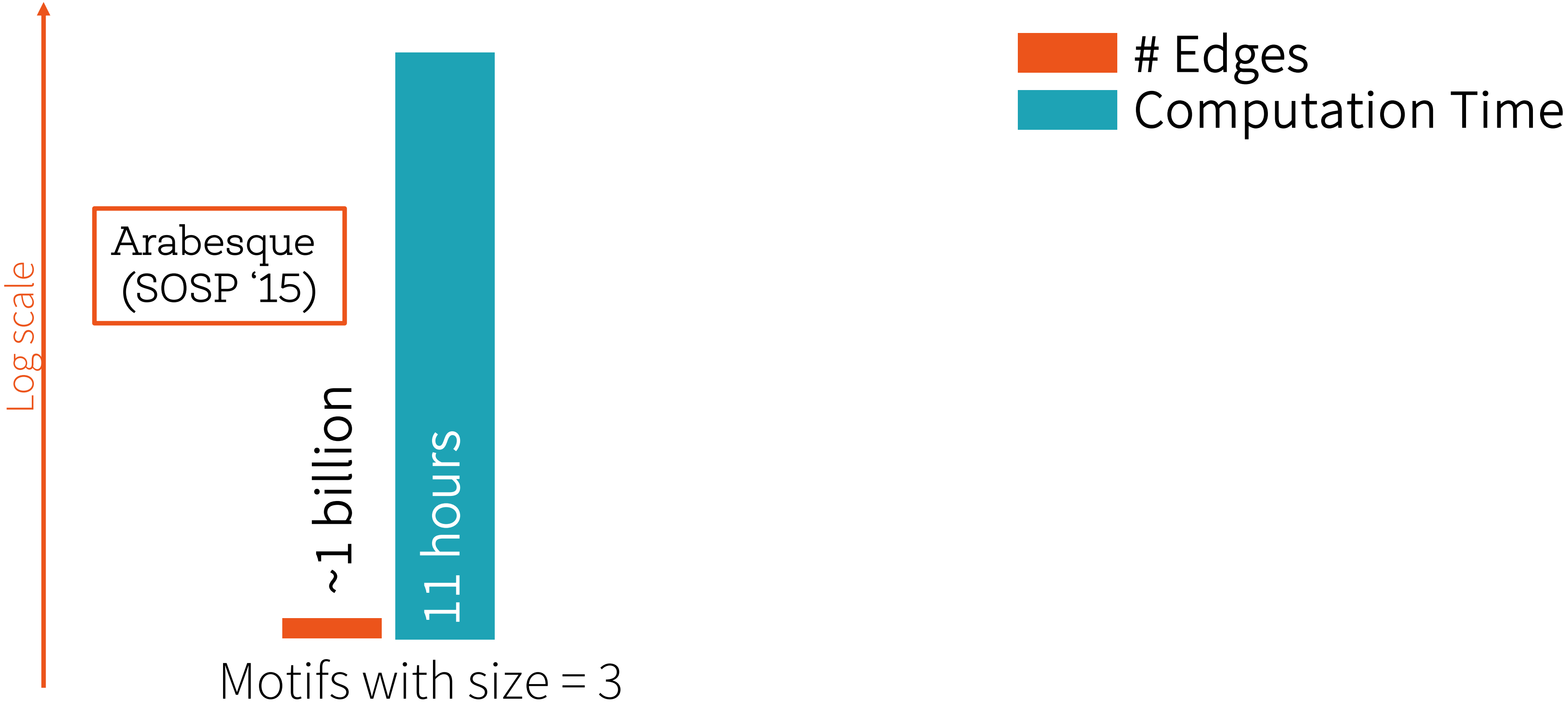

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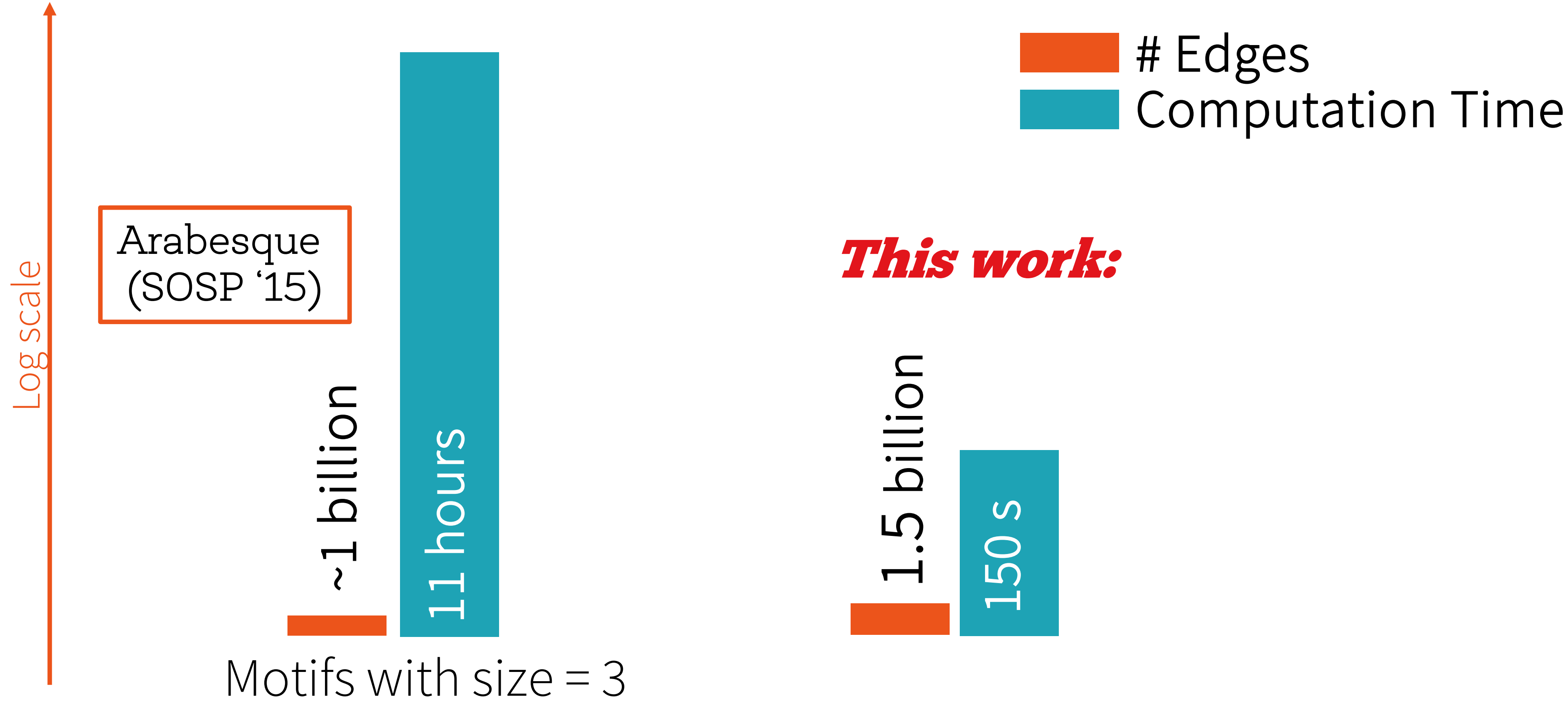

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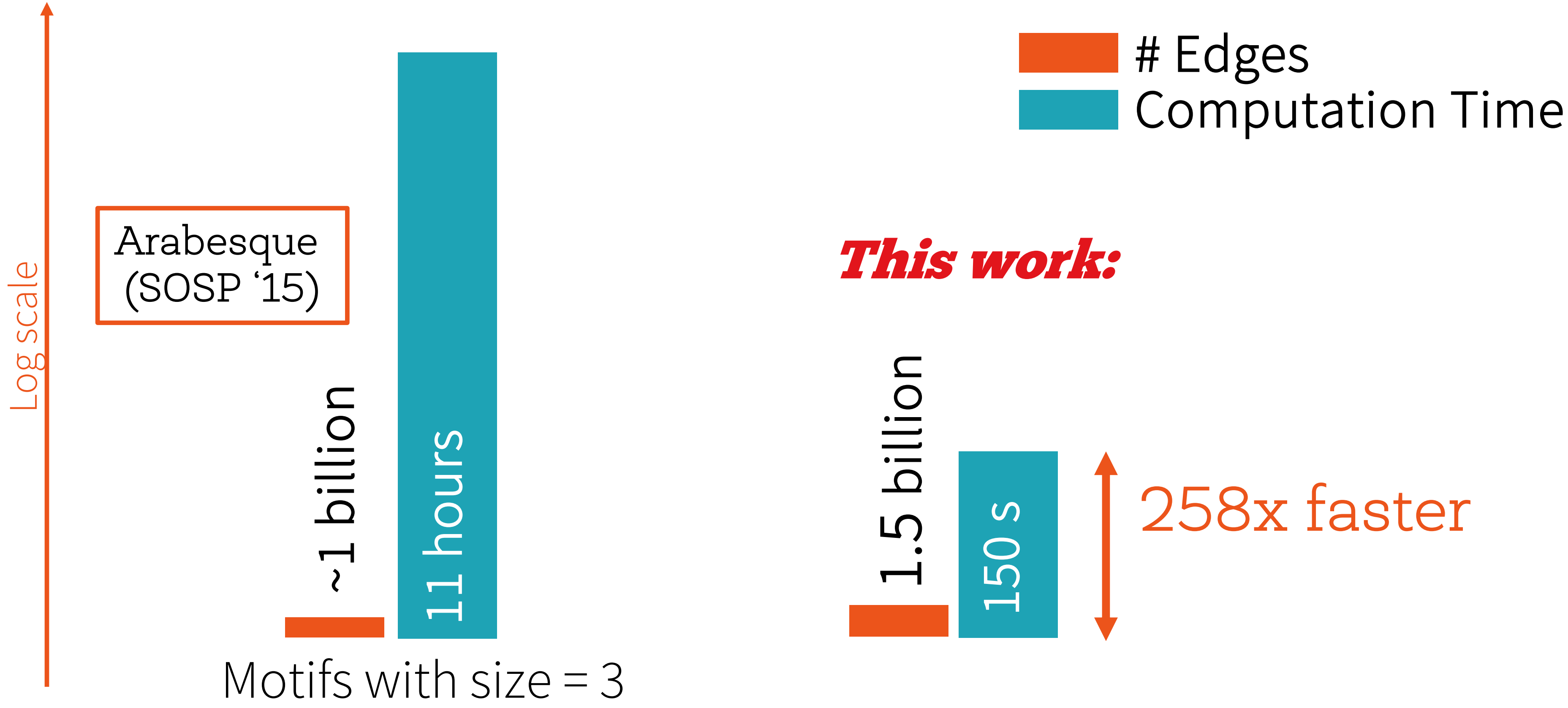

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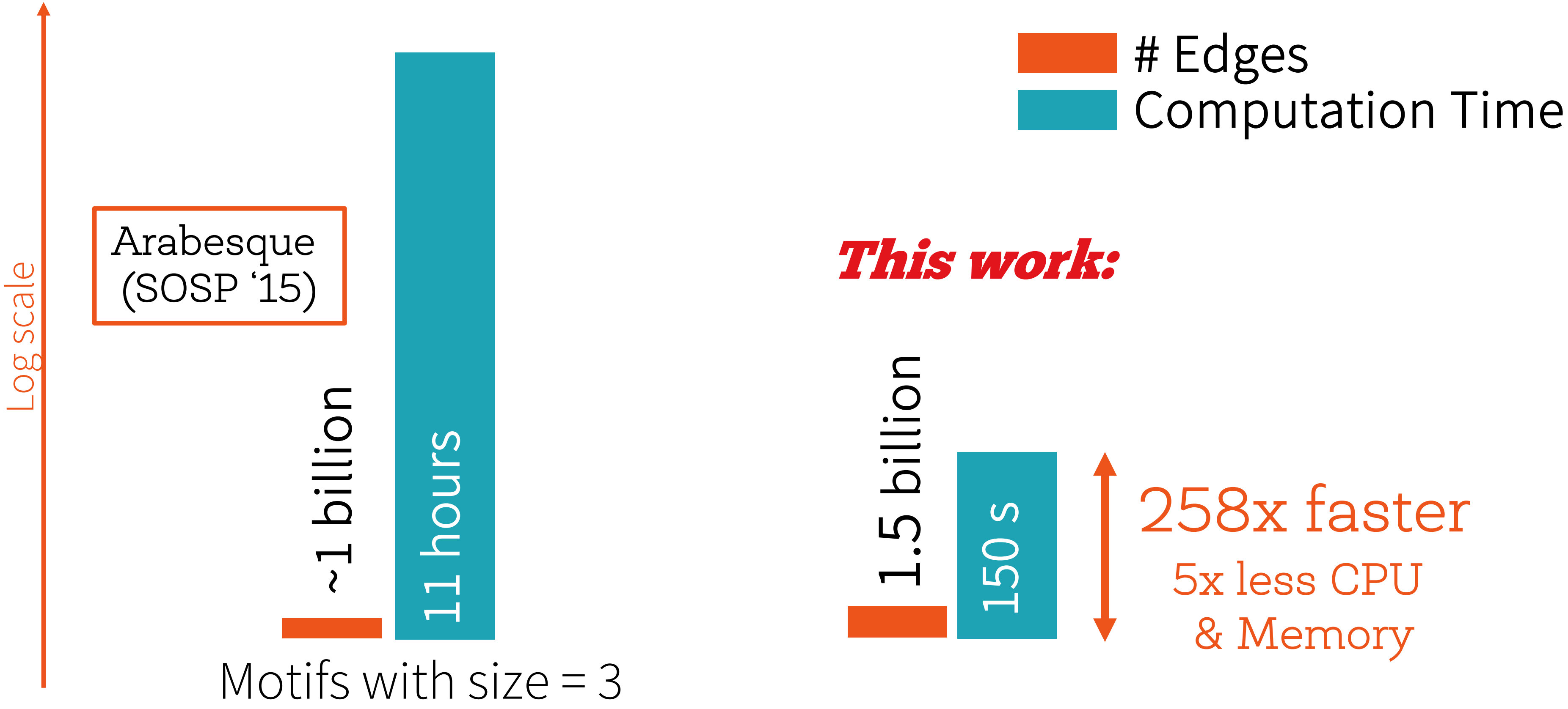

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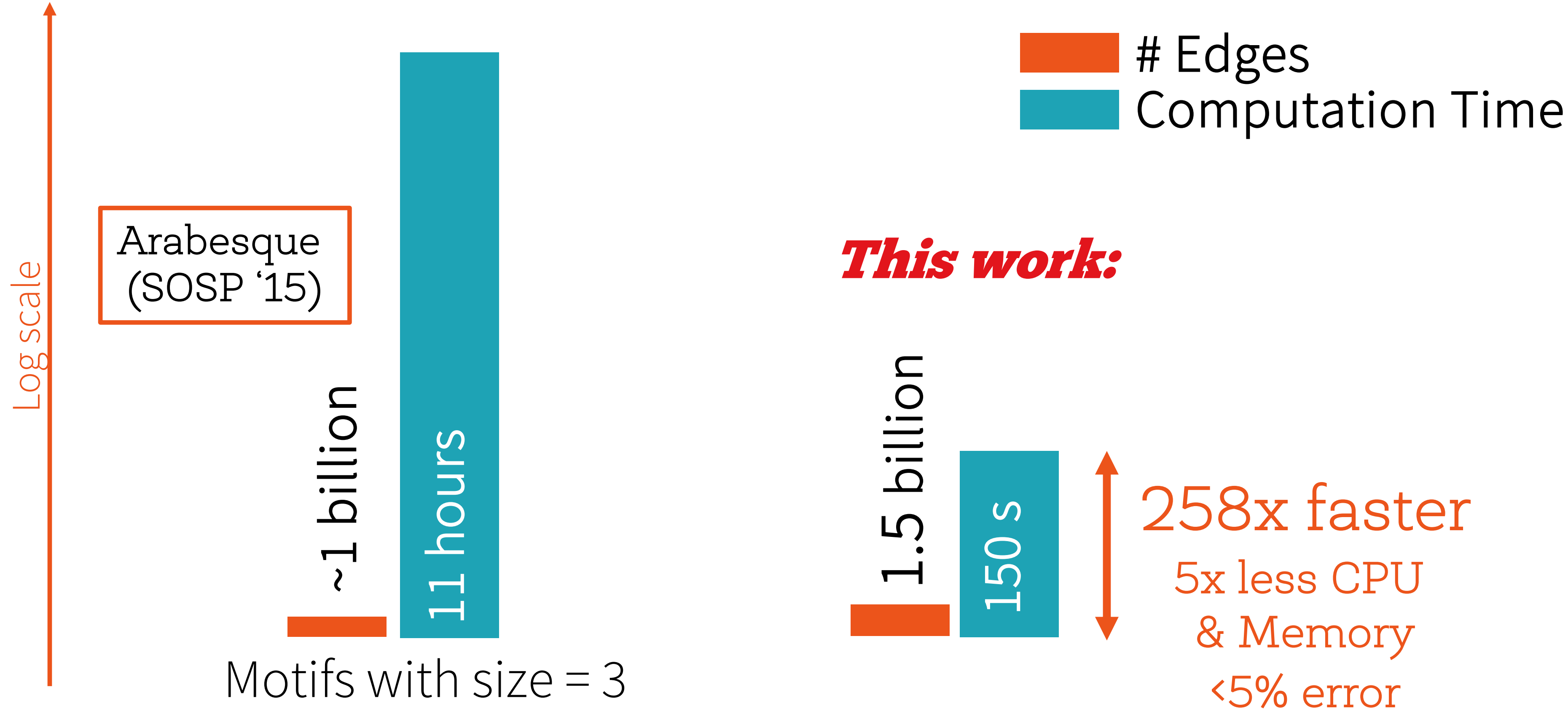

Many mining tasks do not need *exact* answers

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Leverage *approximation* for pattern mining

Approximate Analytics

General approach: Apply algorithm on subset(s) (sample) of the input data

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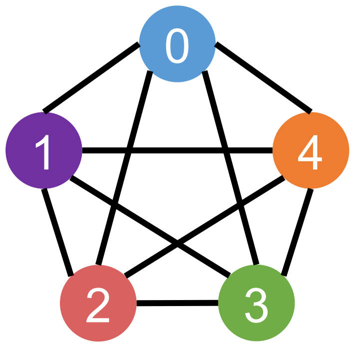

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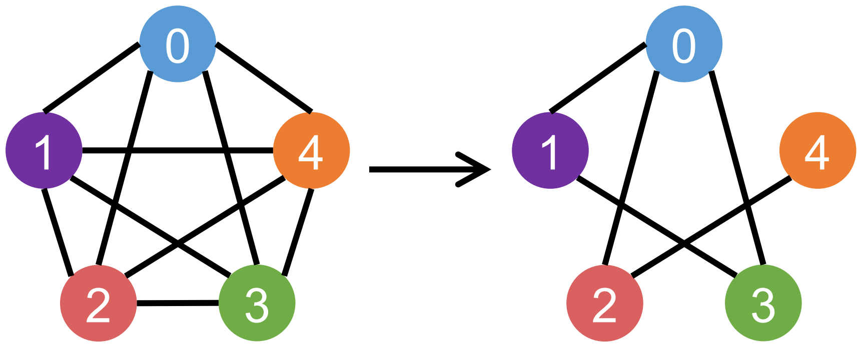
edge sampling
(p=0.5)



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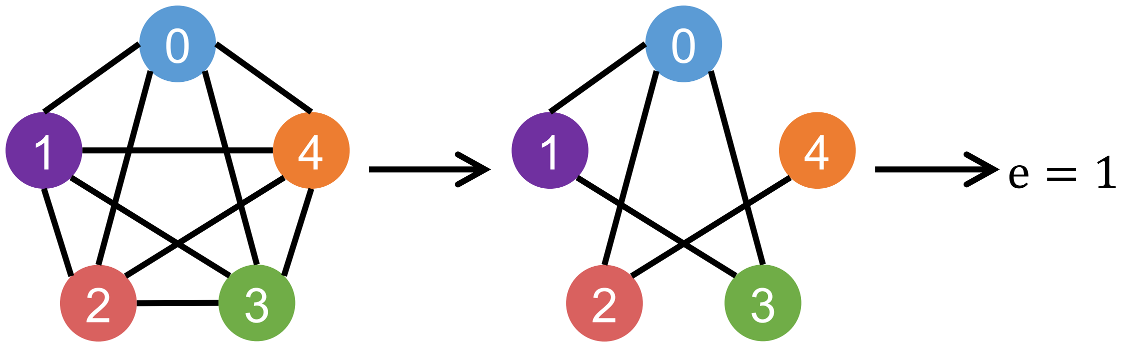
triangle counting



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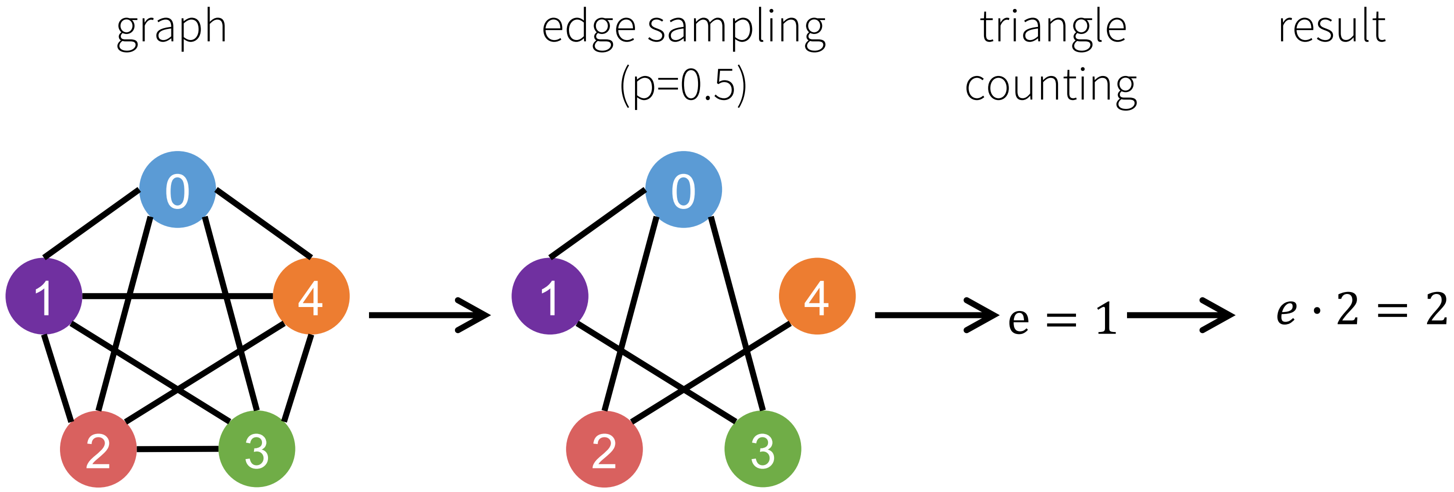

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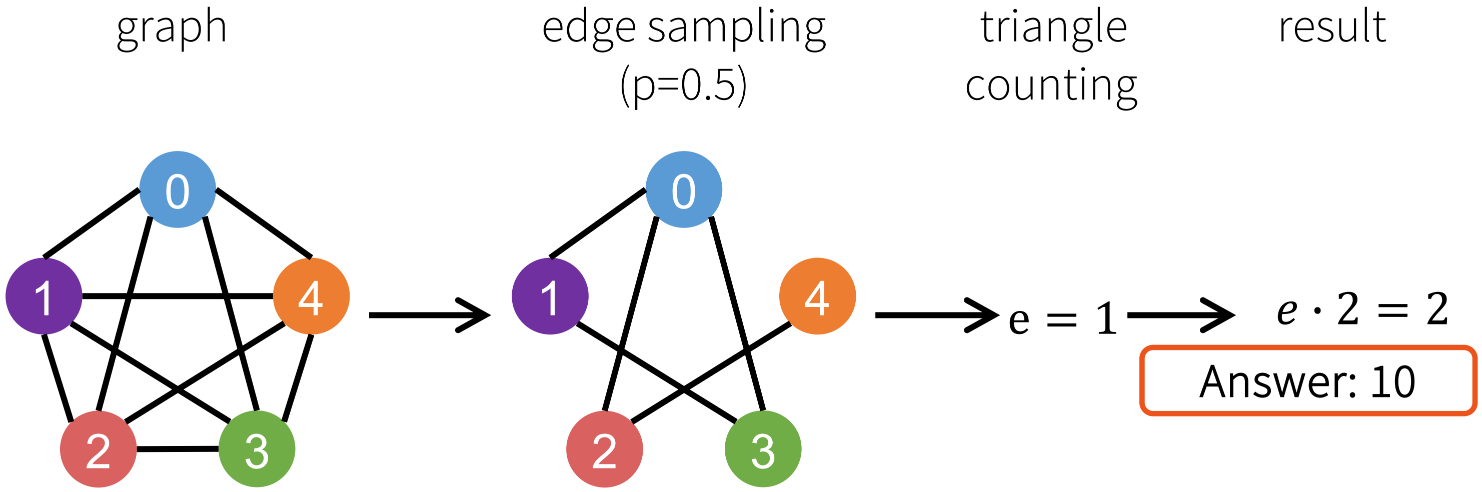

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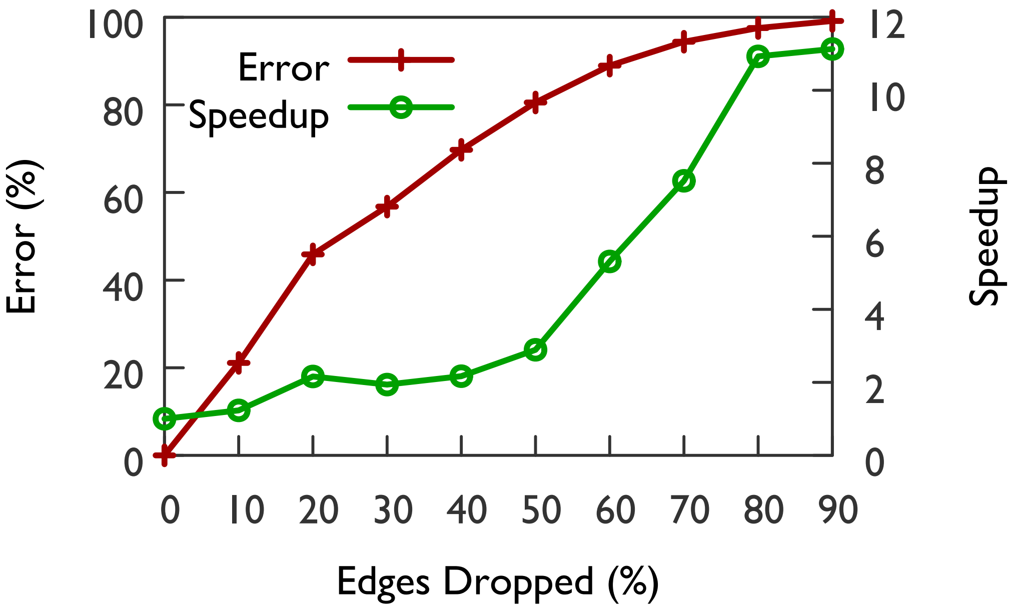

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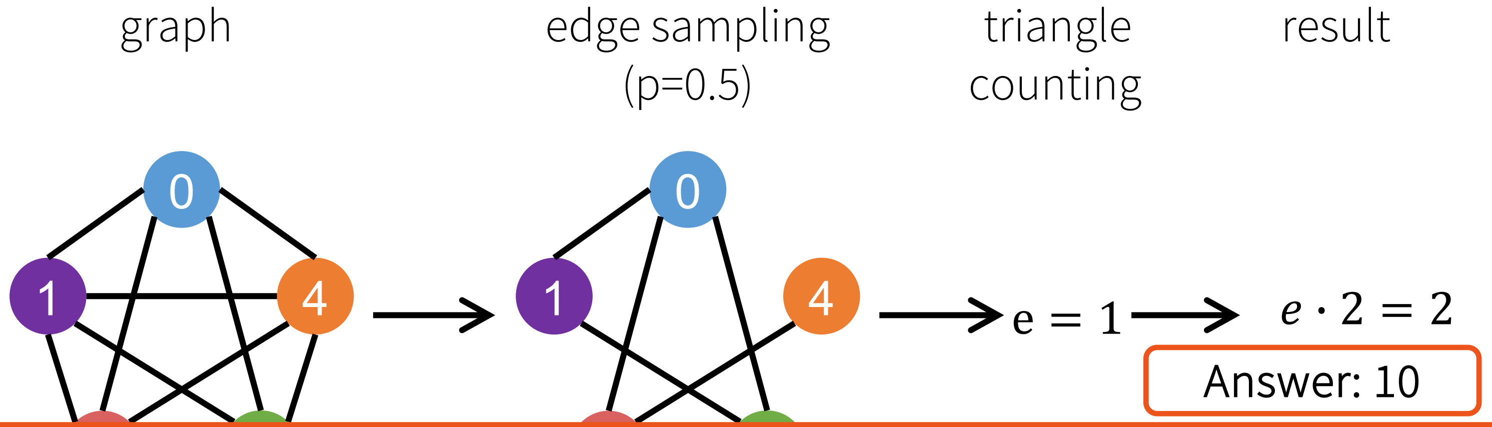

Applying *exact* algorithm on *sampled* graph(s)
not the right approach for pattern mining

ASAP *leverages* existing work in graph approximation theory and makes it *practical*

Graph Pattern Mining Theory

Sample instances of the pattern from the graph stream

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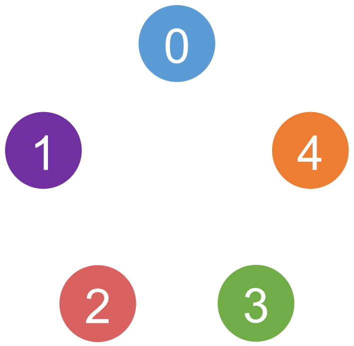

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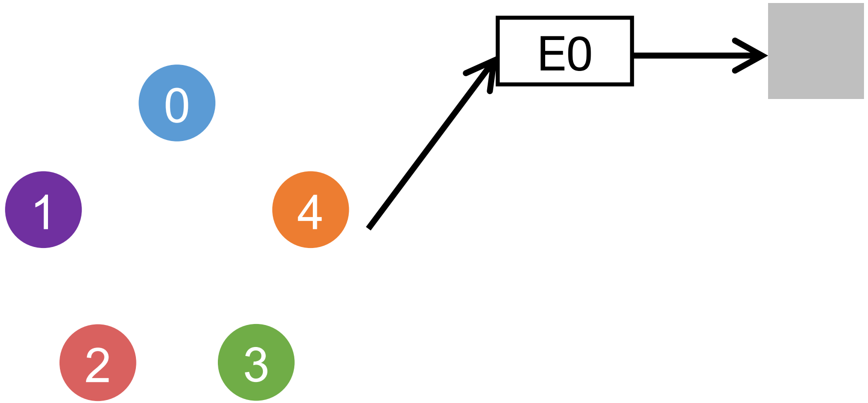

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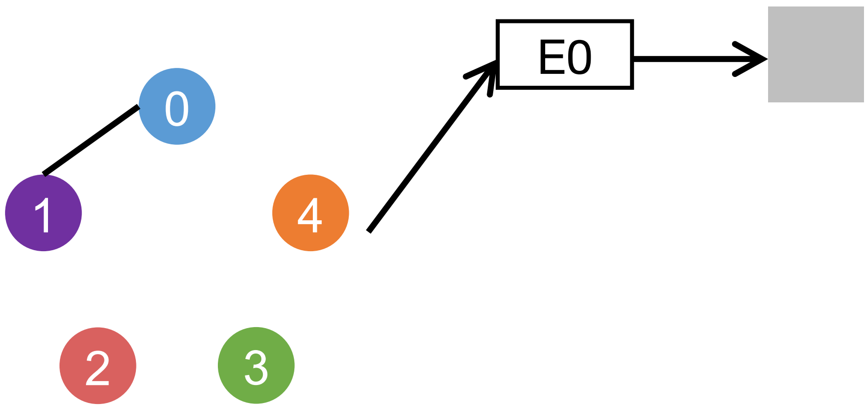

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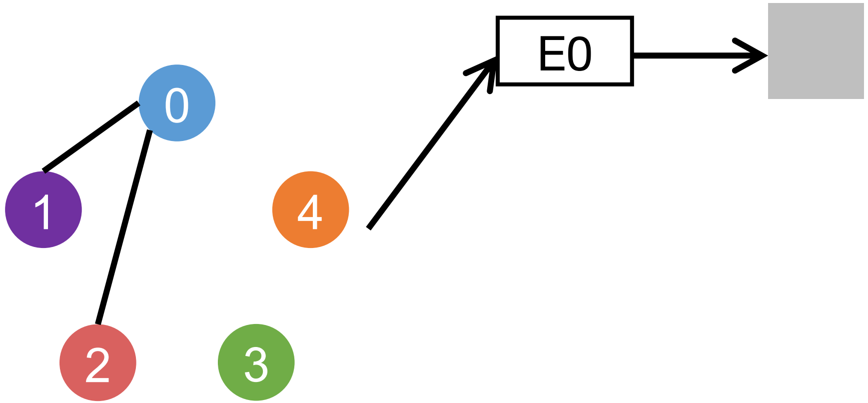

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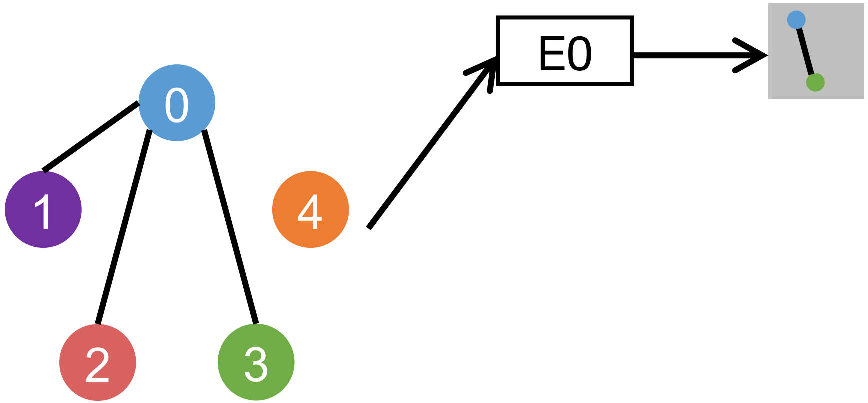

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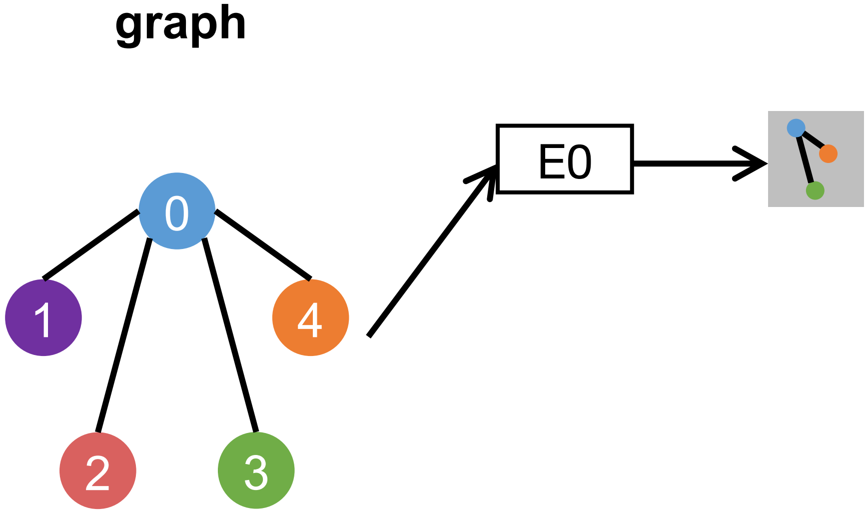

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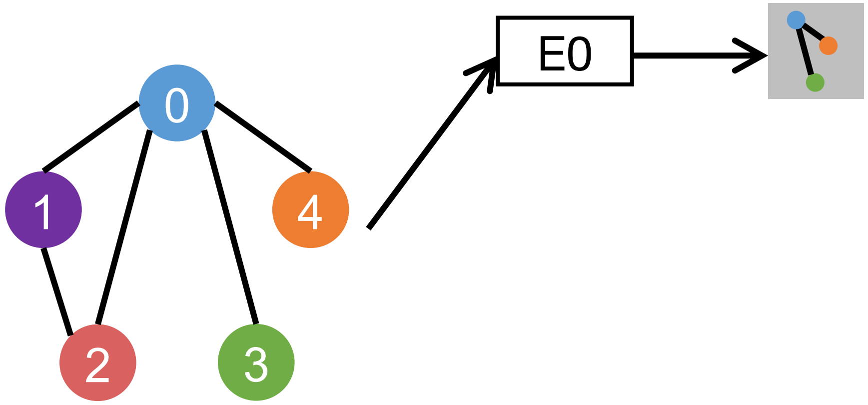

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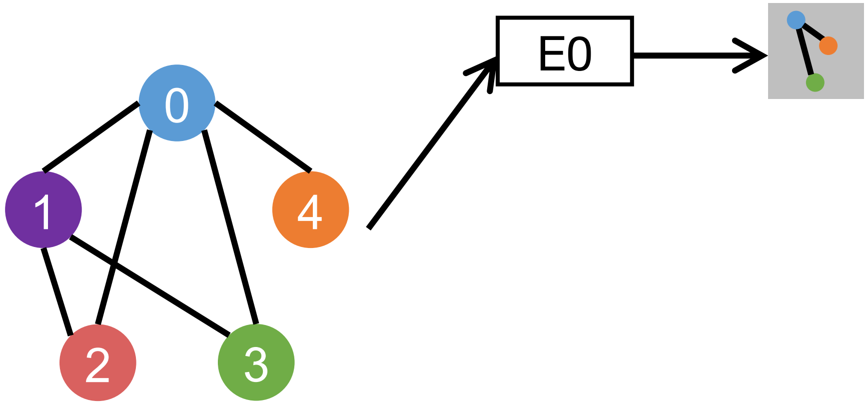

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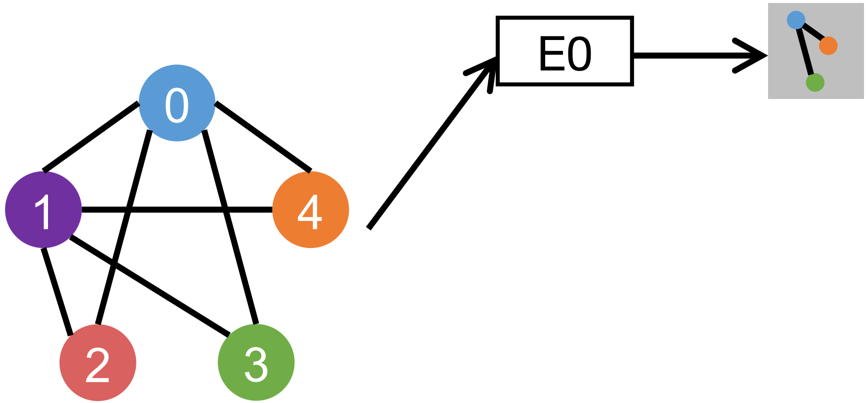

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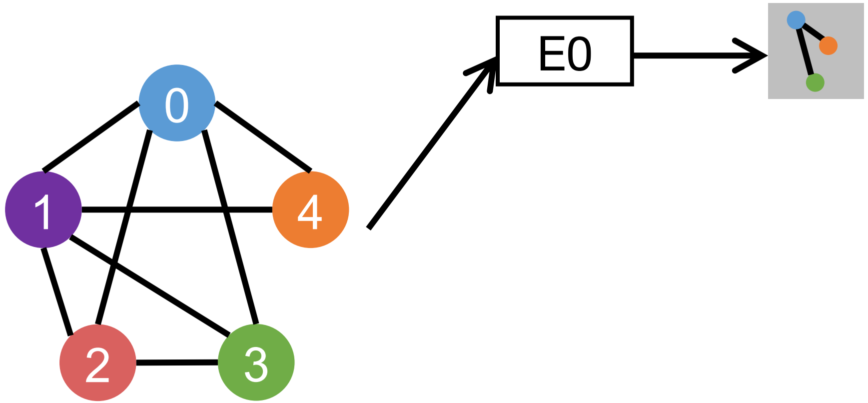

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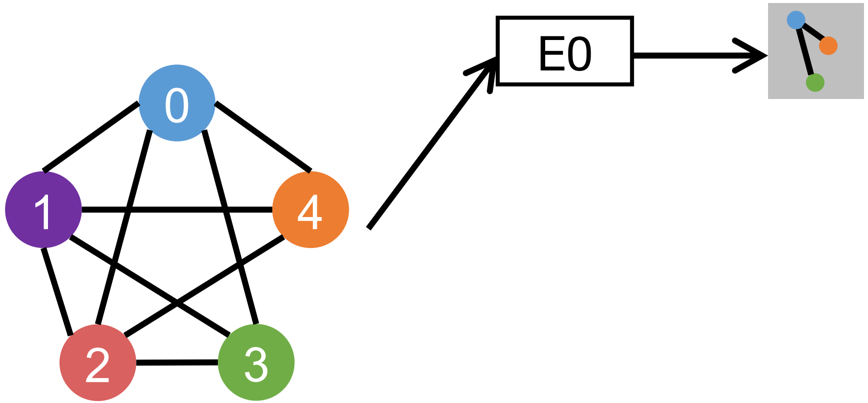

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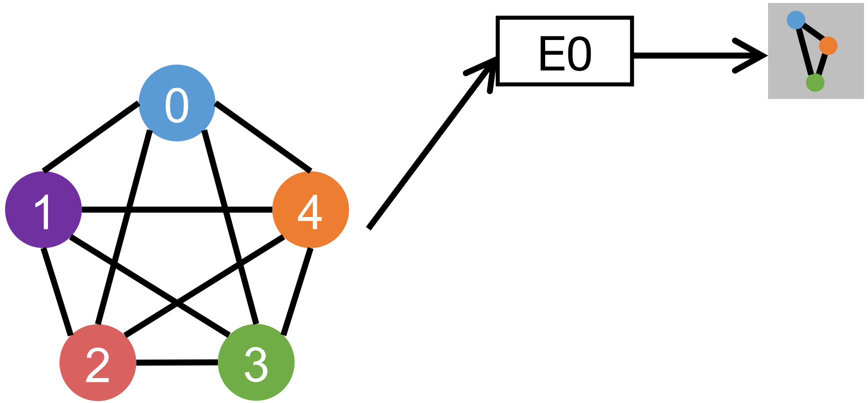

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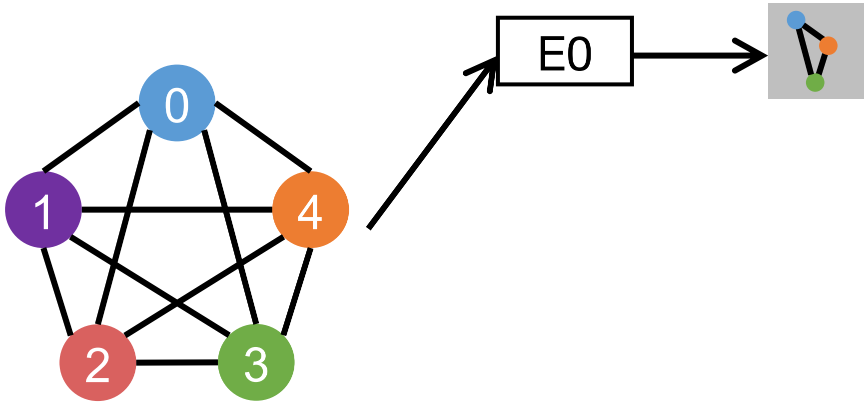

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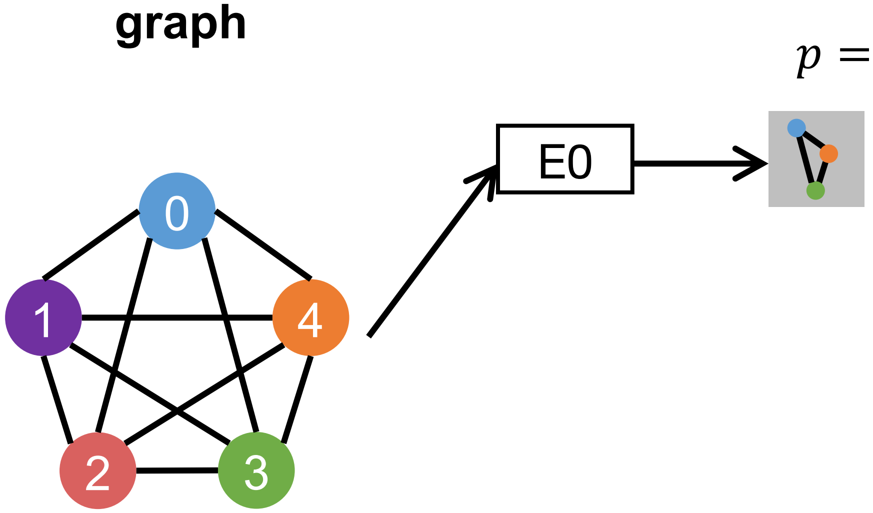

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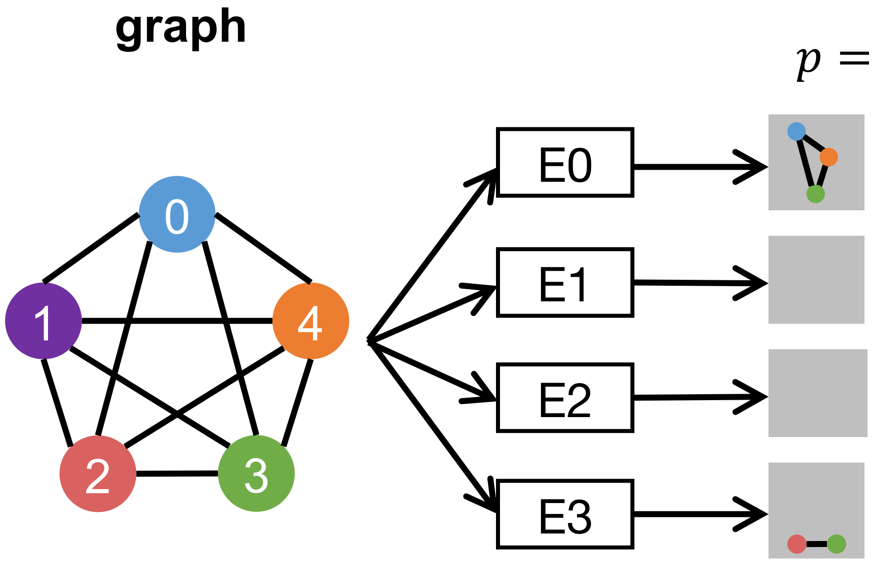

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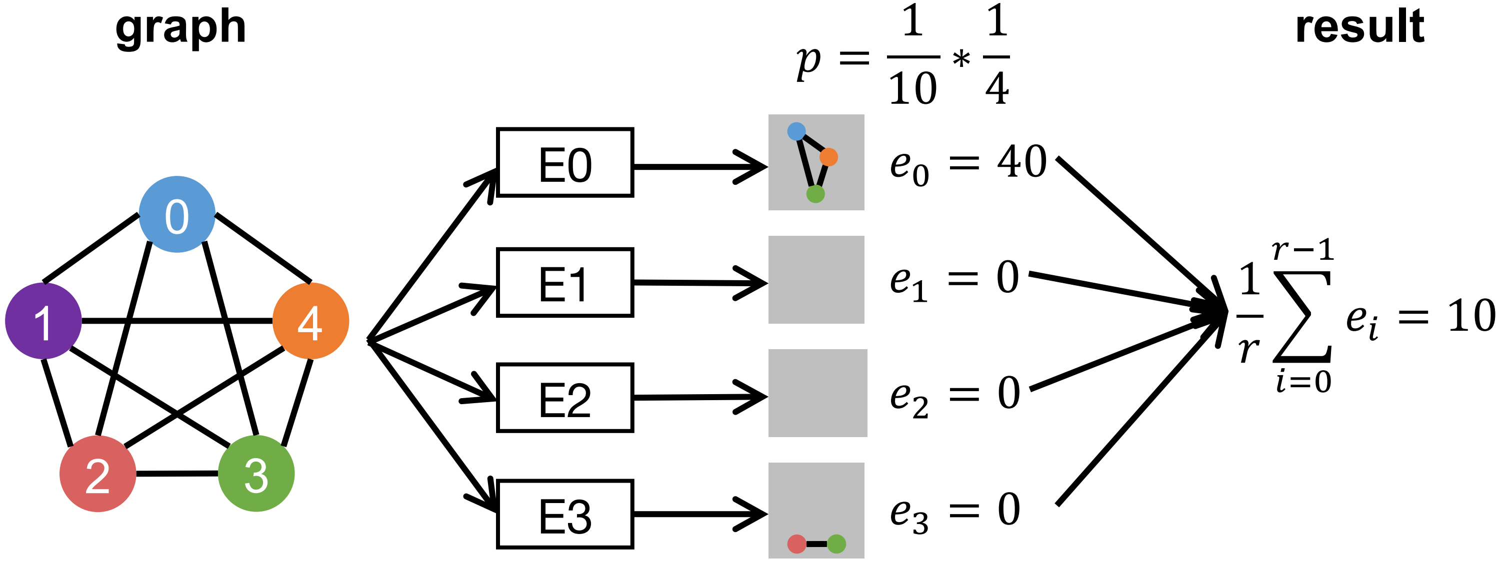

edge stream: (0,1), (0,2), (0,3), (0,4), (1,2), (1,3), (1,4), (2,3), (2,4), (3,4)

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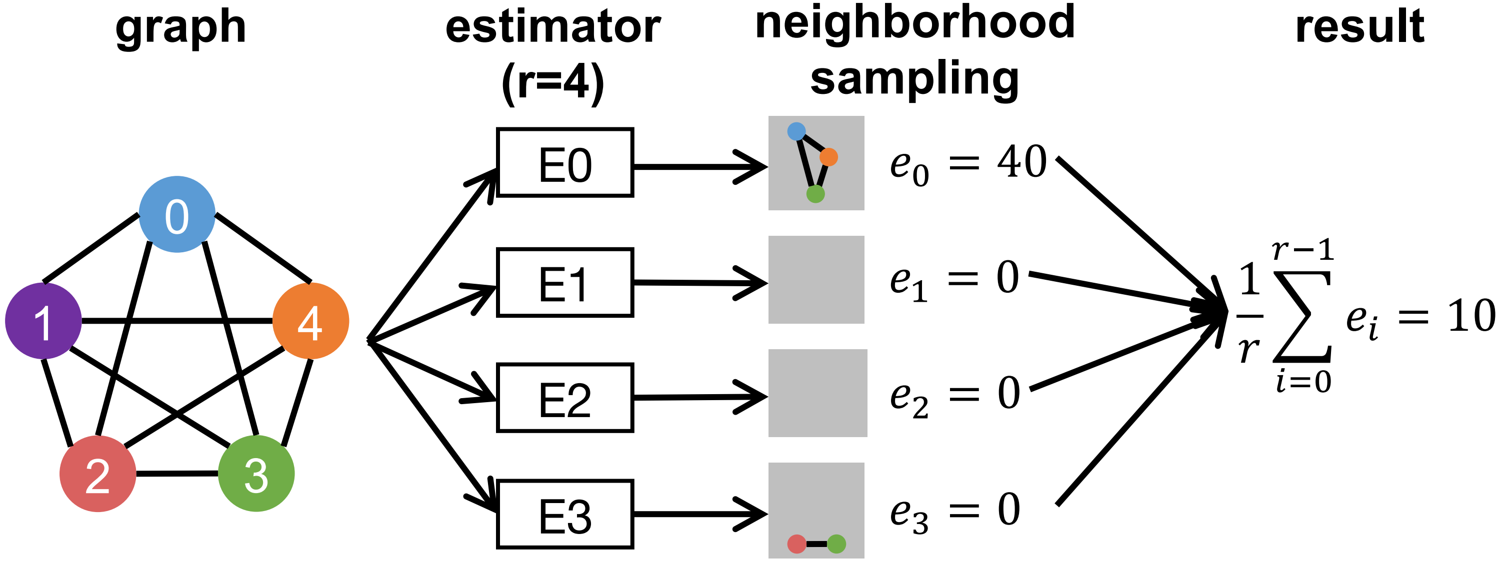

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Pavan et al. Counting and sampling triangles from a graph stream, VLDB 2013

A Swift Approximate Pattern miner

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graphA.patterns("a->b->c", "100s")
graphB.fourClique("5.0%","95.0%")
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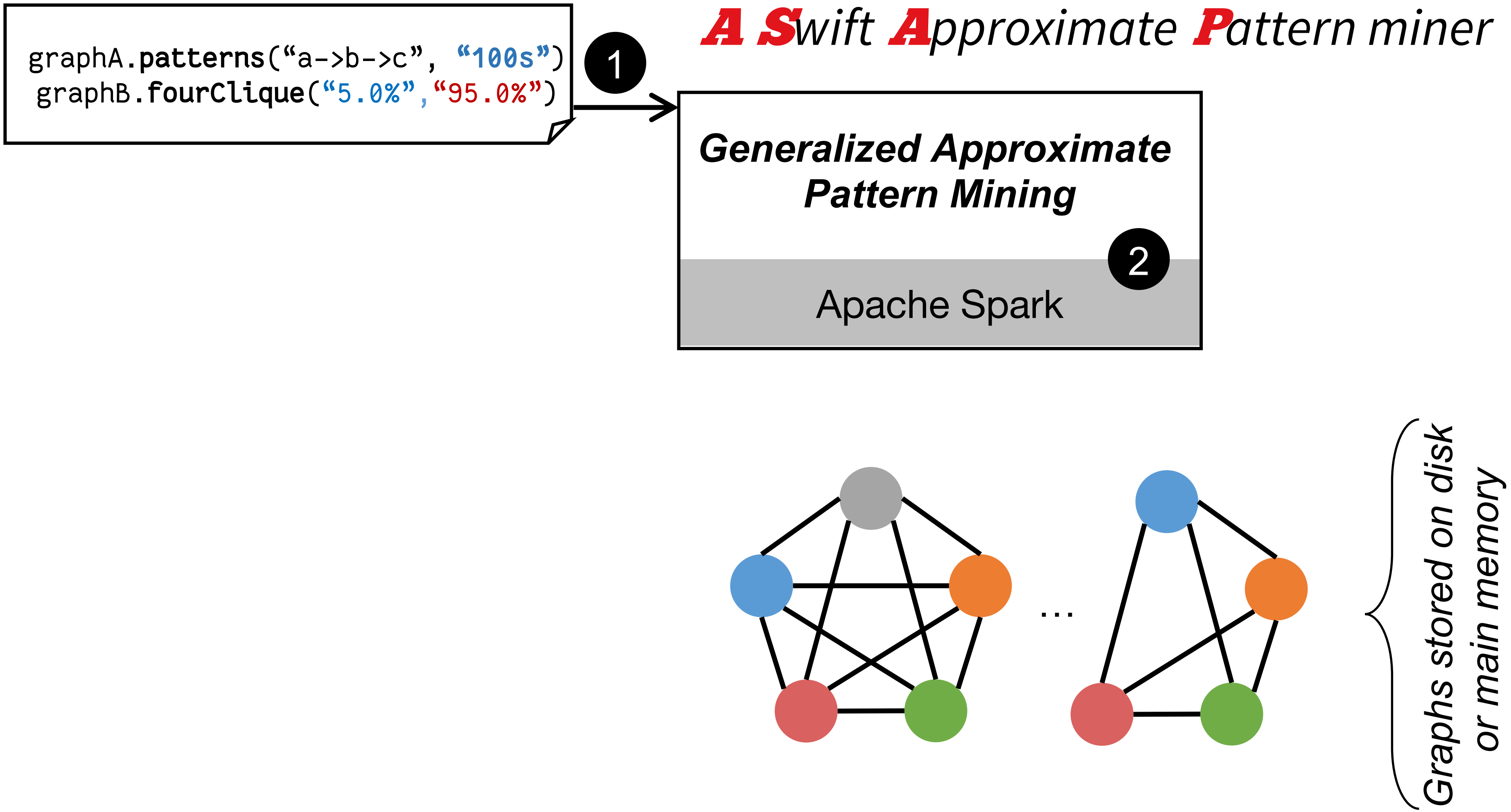
1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Generalized Approximate Pattern Mining
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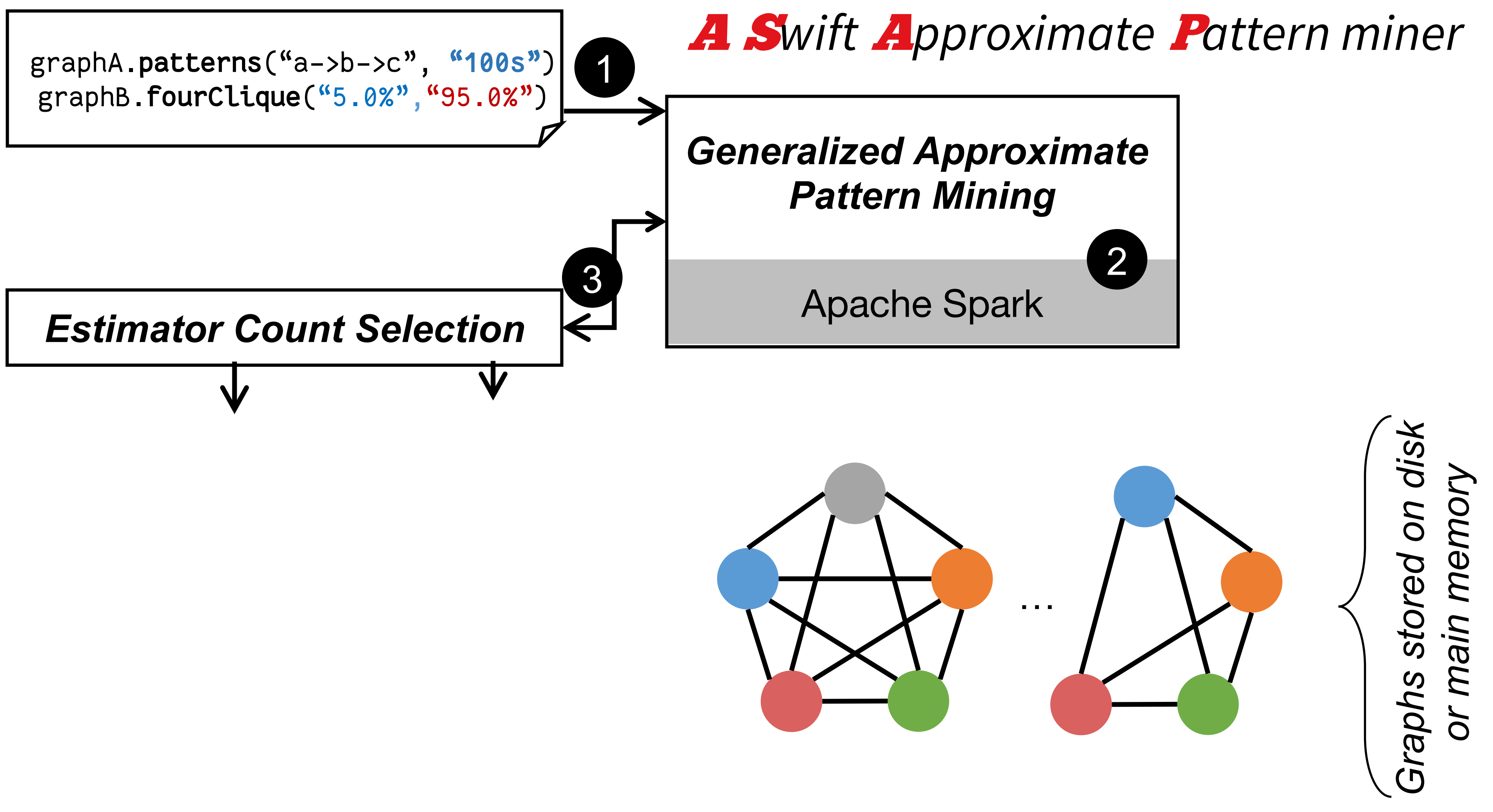
Graphs stored on disk or main memory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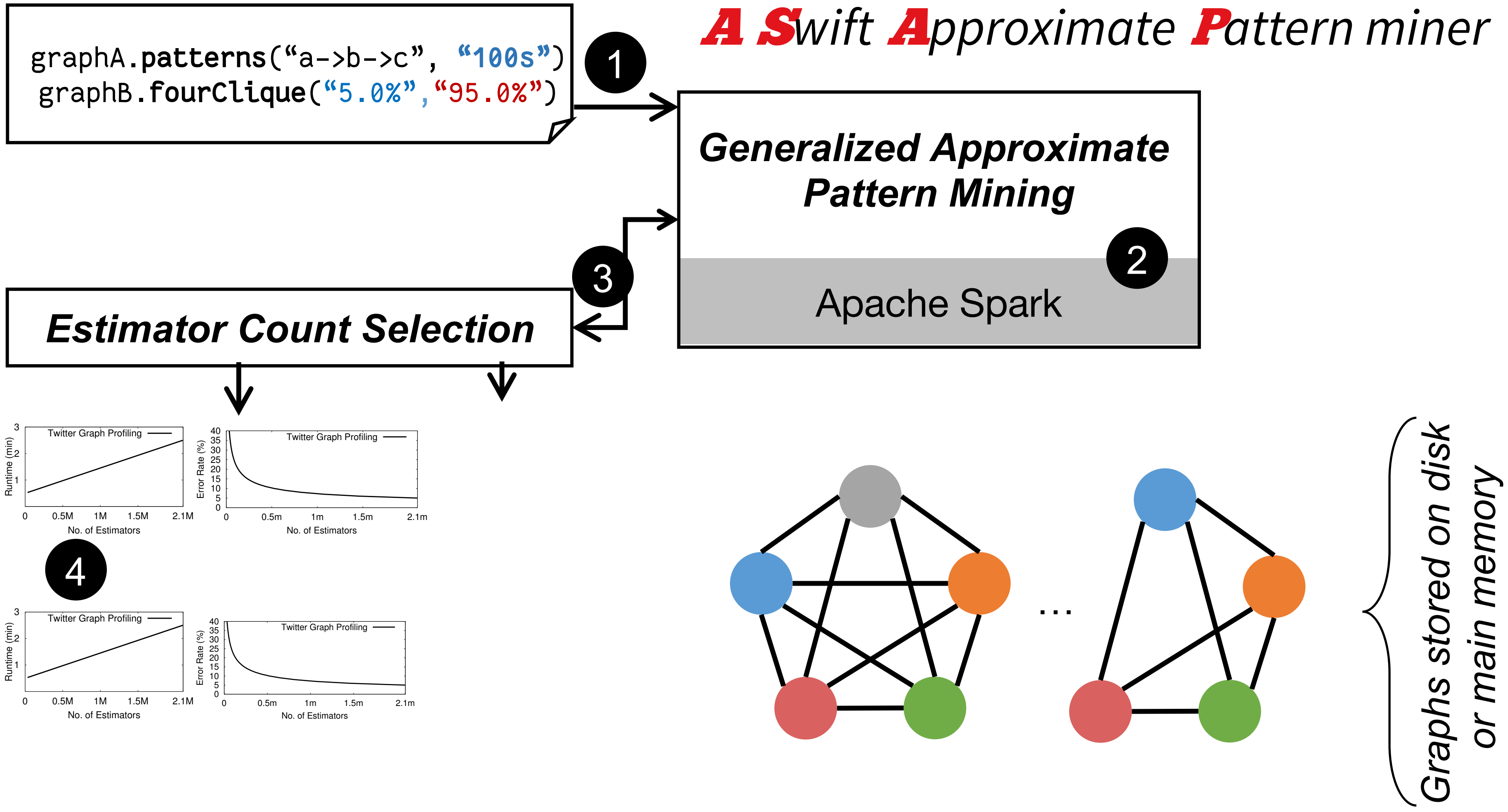
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Twitter Graph Profiling
Runtime (min)
No. of Estimators
Error Rate (%)
...
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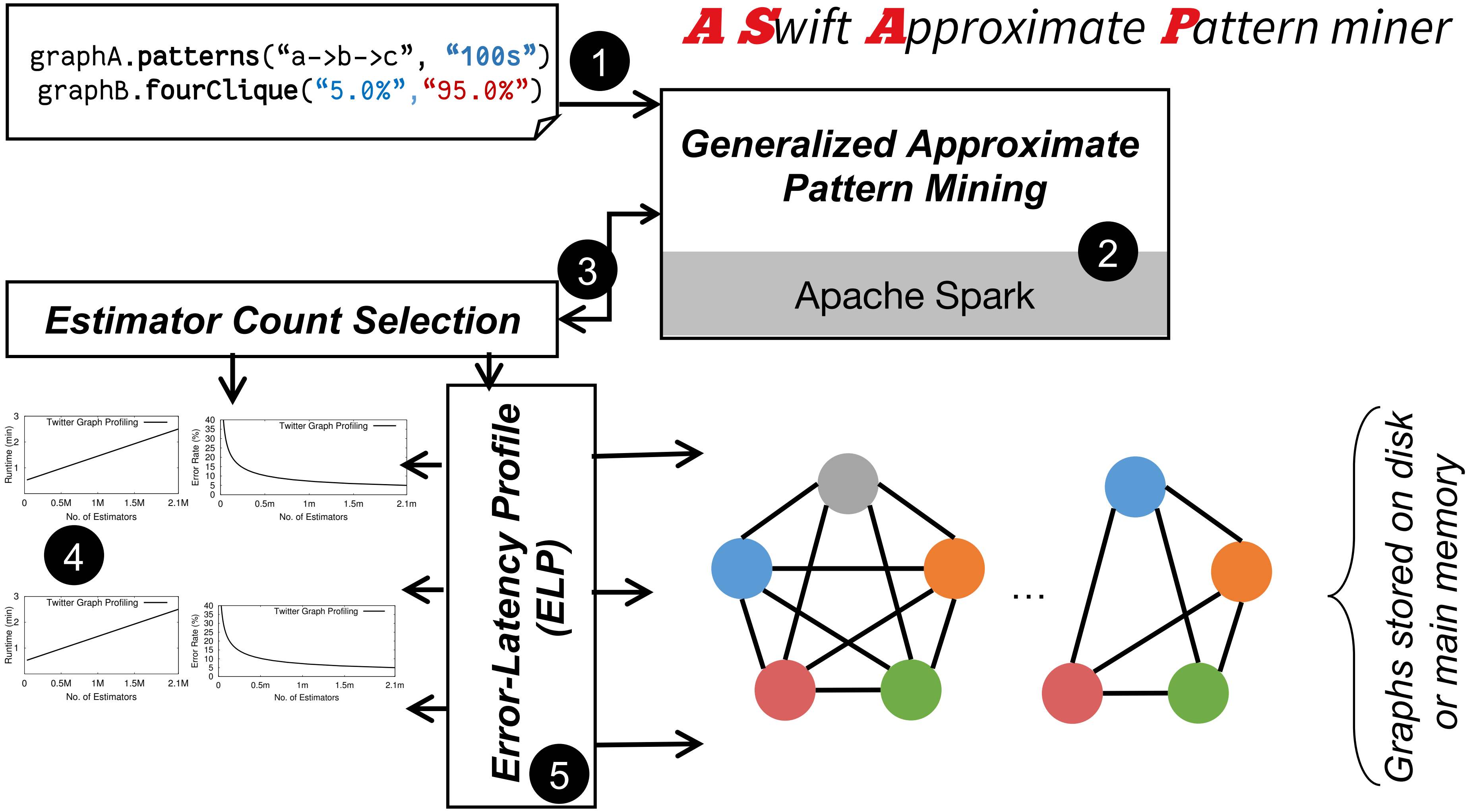
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Error-Latency Profile (ELP)
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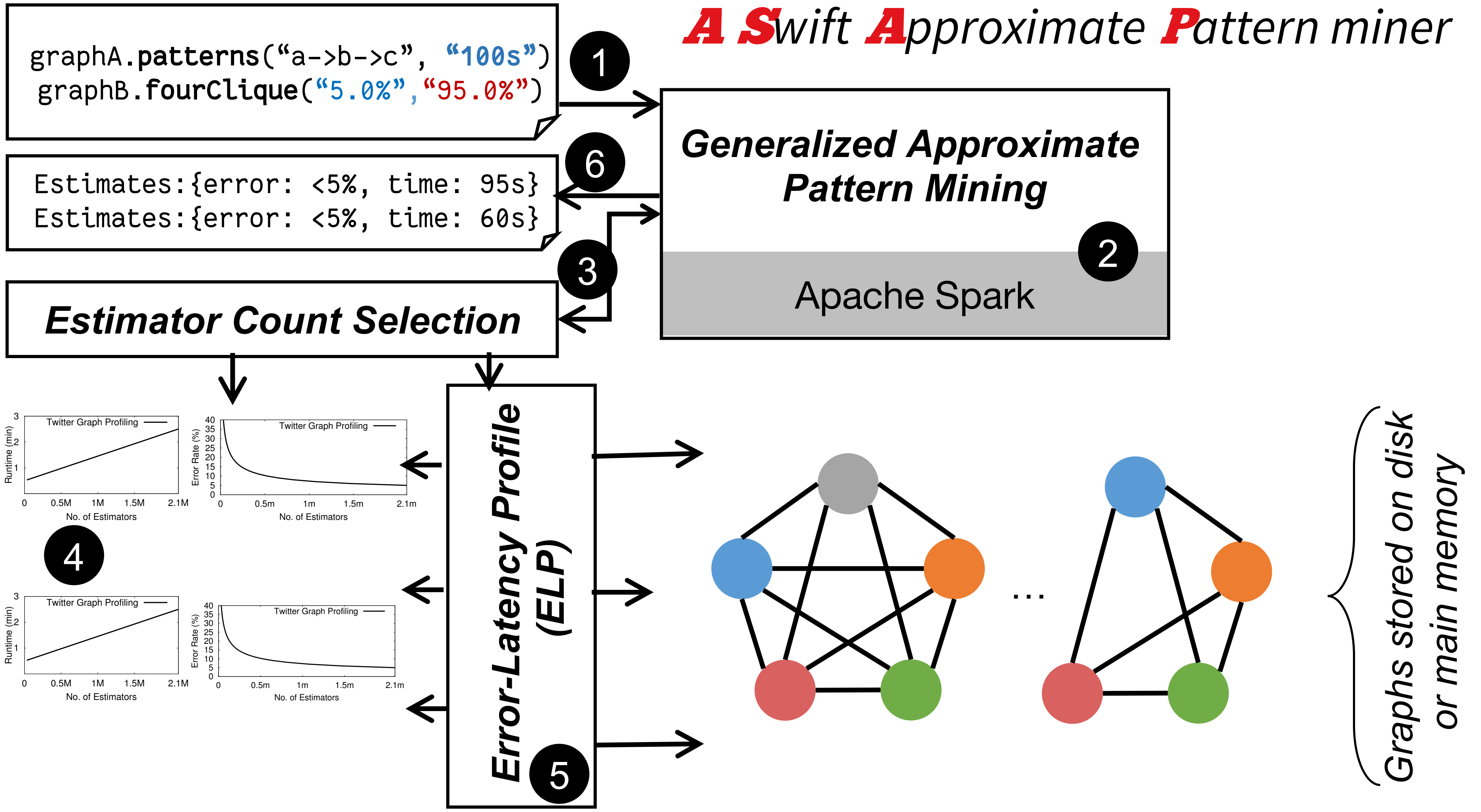

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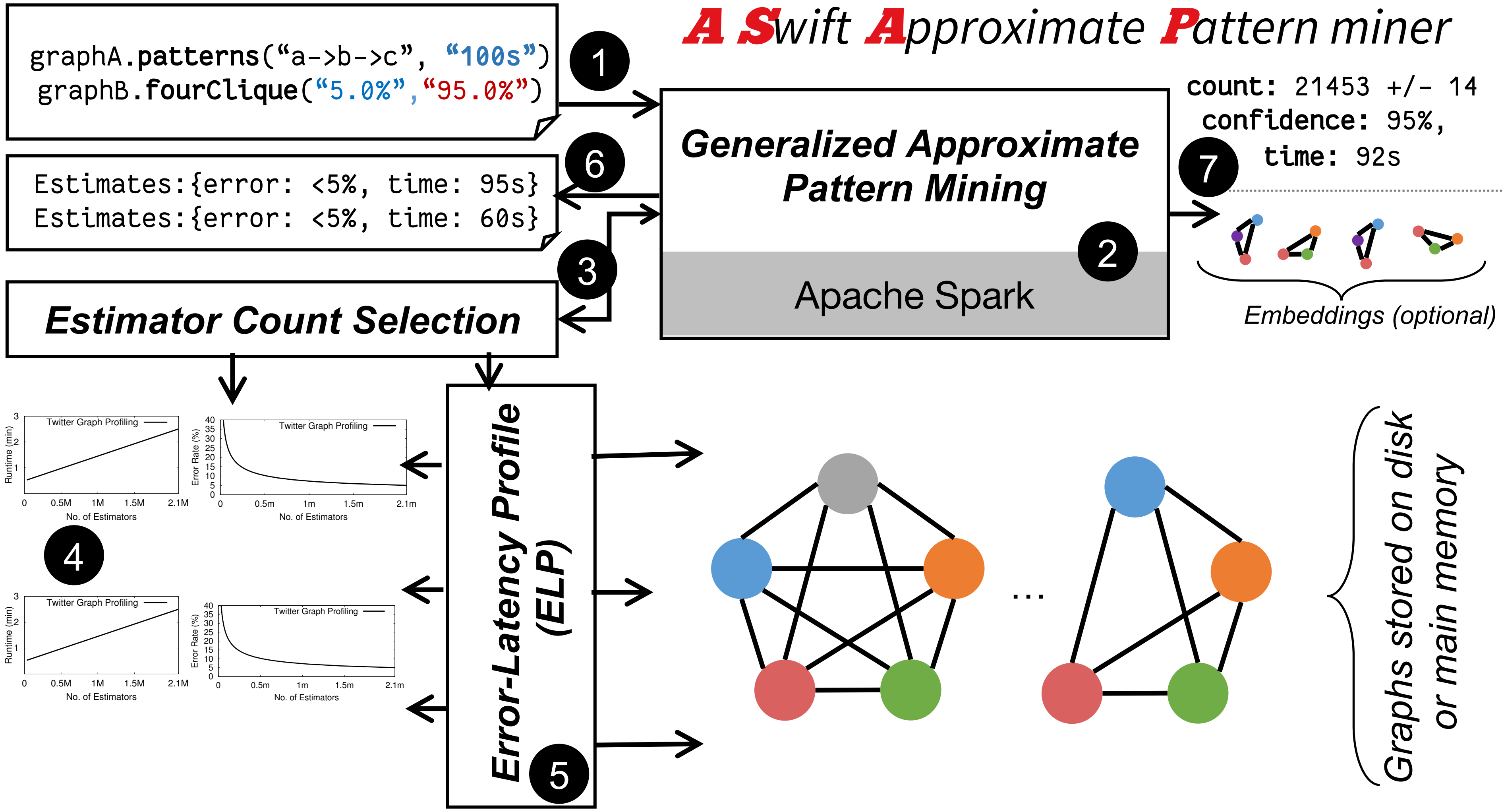

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Generalized Approximate Pattern Mining
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count: 21453 +/- 14
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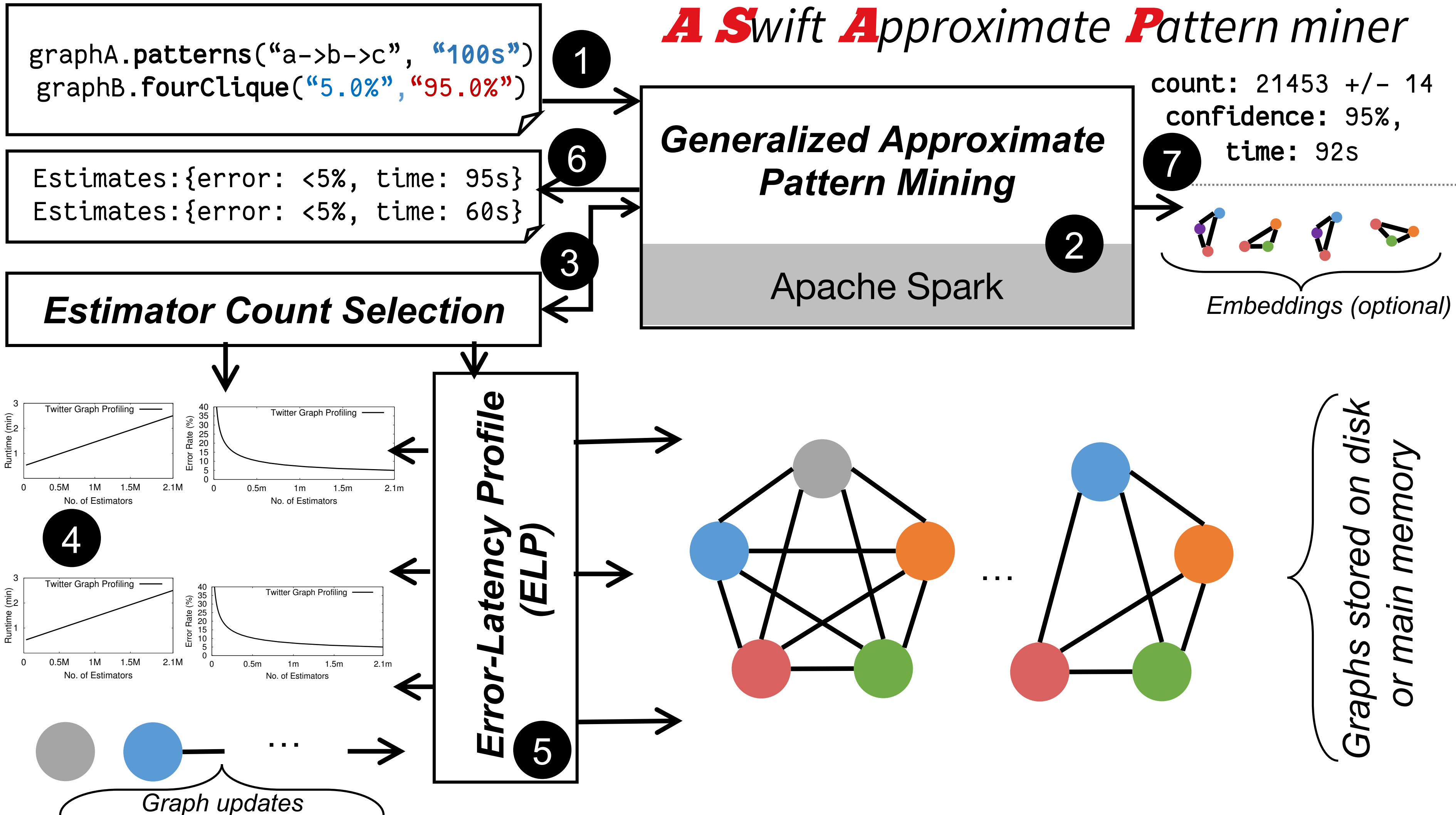
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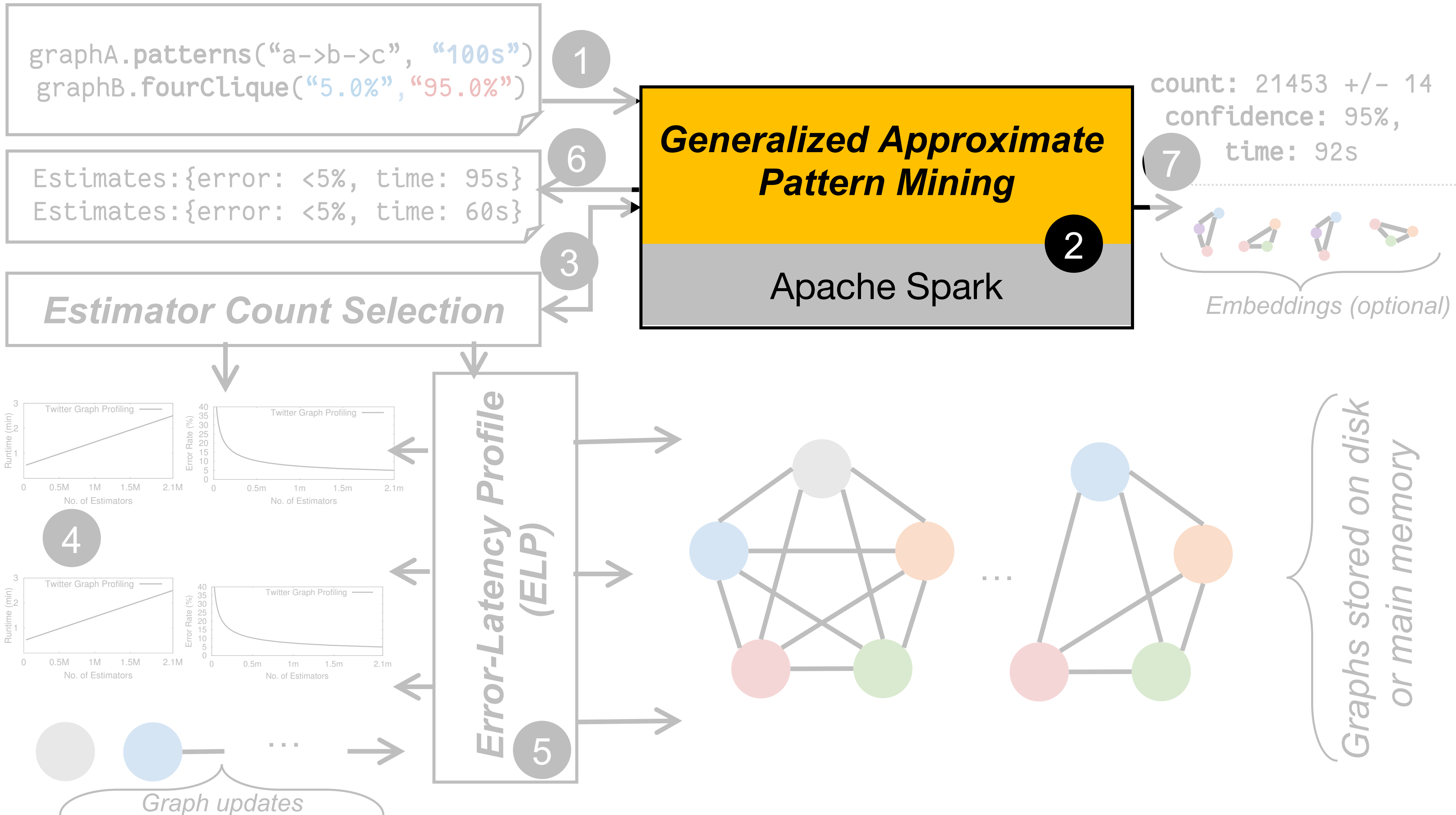
Graph updates
Graphs stored on disk or main memory



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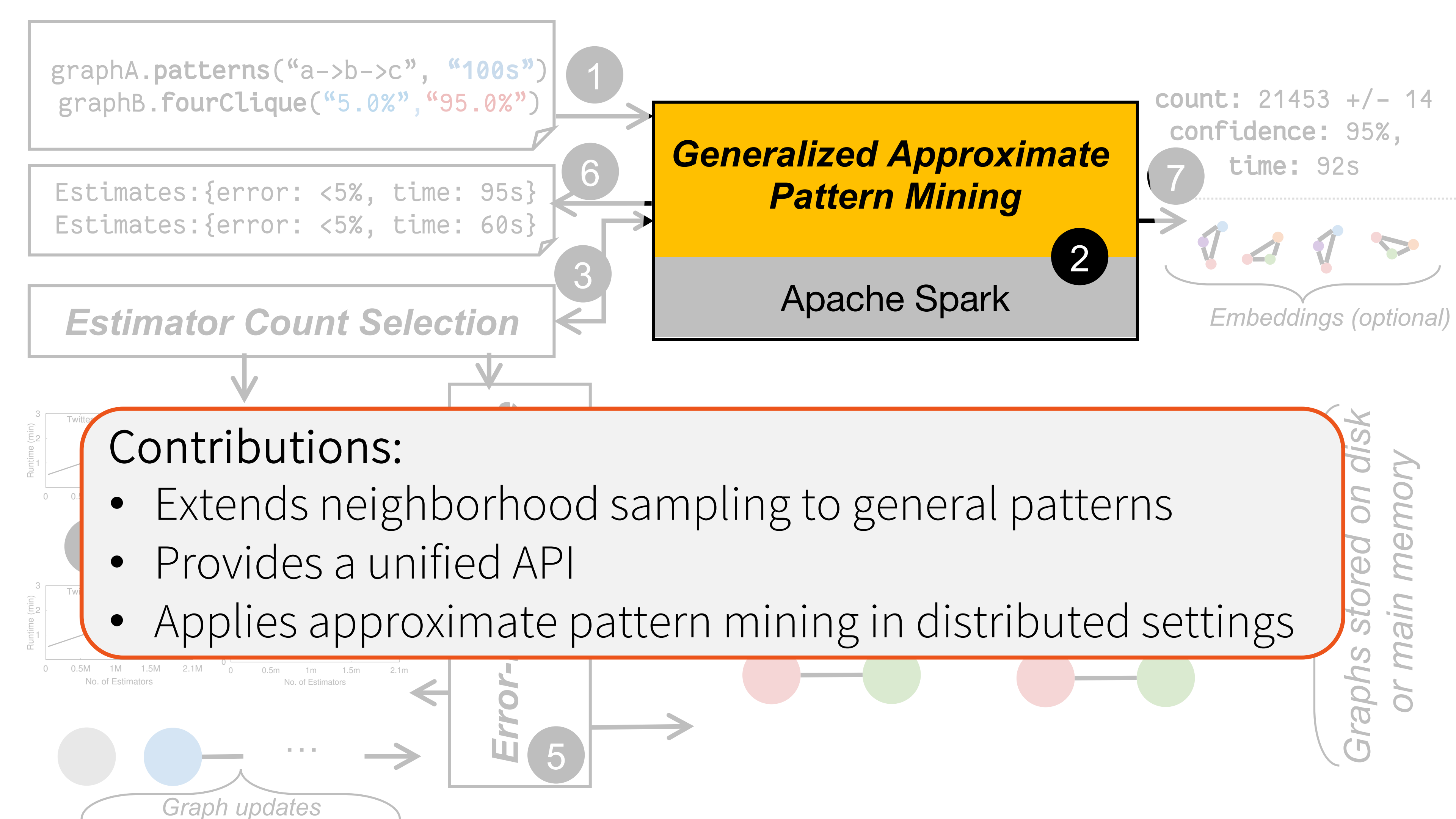
Graphs stored on disk or main memory
Graph updates



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Contributions:
• Extends neighborhood sampling to general patterns
• Provides a unified API
• Applies approximate pattern mining in distributed settings
No. of Estimators
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Graph updates
Graphs stored on disk or main memory

Generalized Approximate Pattern Mining

Developers write a single estimator using ASAP's API

API	**Description**
`sampleVertex: ()`$\rightarrow(v, p)$	Uniformly sample one vertex from the graph.
`SampleEdge: ()`$\rightarrow(e, p)$	Uniformly sample one edge from the graph.
`ConditionalSampleVertex: (subgraph)`$\rightarrow(v, p)$	Uniformly sample a vertex that appears after a sampled subgraph.
`ConditionalSampleEdge: (subgraph)`$\rightarrow(e, p)$	Uniformly sample an edge that is adjacent to the given subgraph and comes after the subgraph in the order.
`ConditionalClose: (subgraph, subgraph)`$\rightarrow boolean$	Given a sampled subgraph, check if another subgraph that appears later in the order can be formed.

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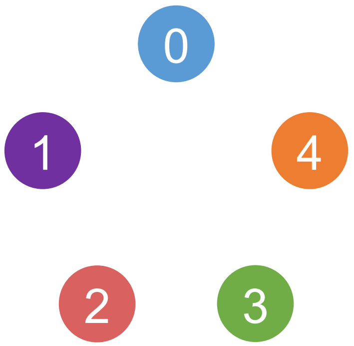

SampleTriangle

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(e1, p1) = sampleEdge()
(e2, p2) = conditionalSampleEdge(Subgraph(e1))
if (!e2) return 0
subgraph1 = Subgraph(e1, e2)
subgraph2 = Triangle(e1, e2)-subgraph1
if conditionalClose(subgraph1, subgraph2)
  return 1/(p1.p2)
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edge stream: (0,1), (0,2), (0,3), (0,4), (1,2), (1,3), (1,4), (2,3), (2,4), (3,4)

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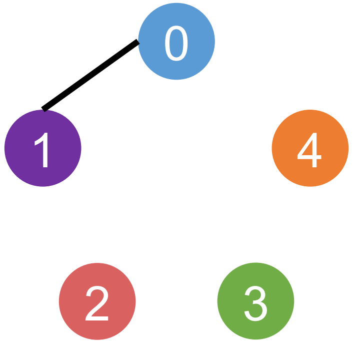

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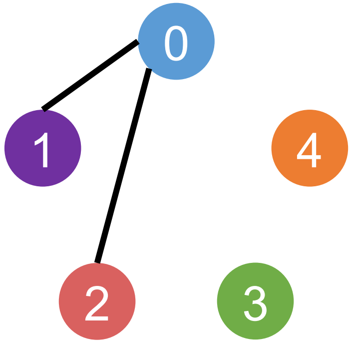

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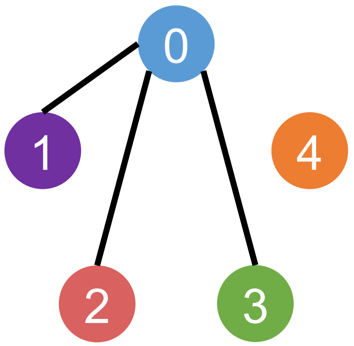

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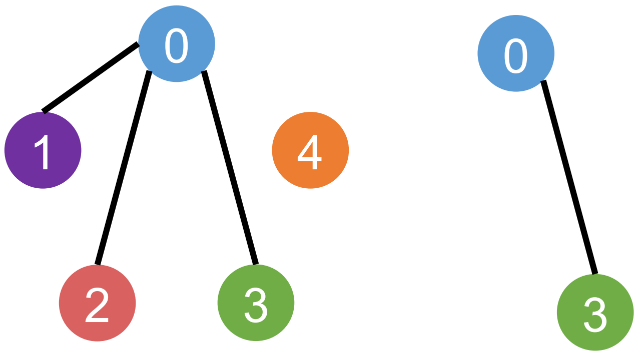

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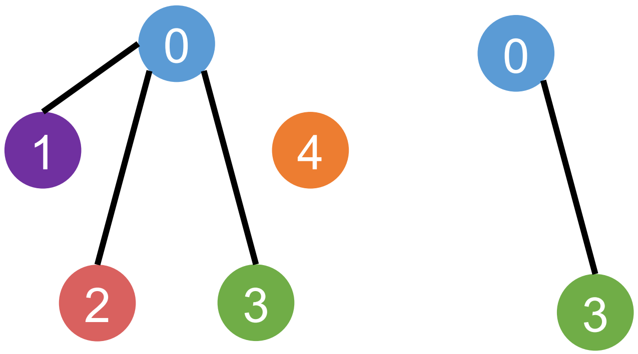

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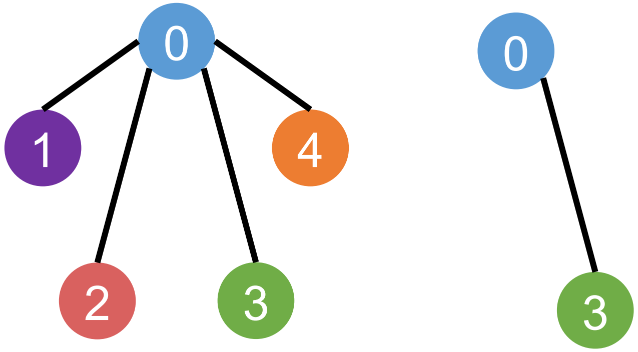

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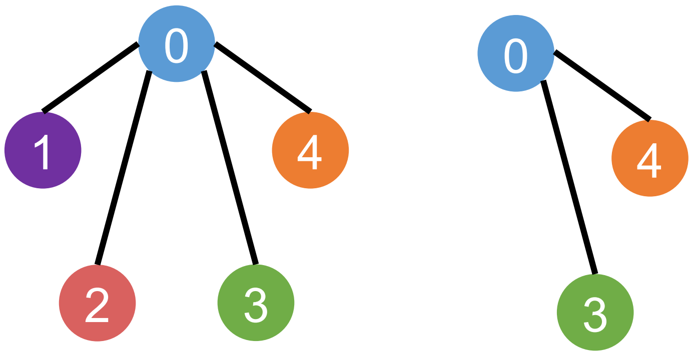

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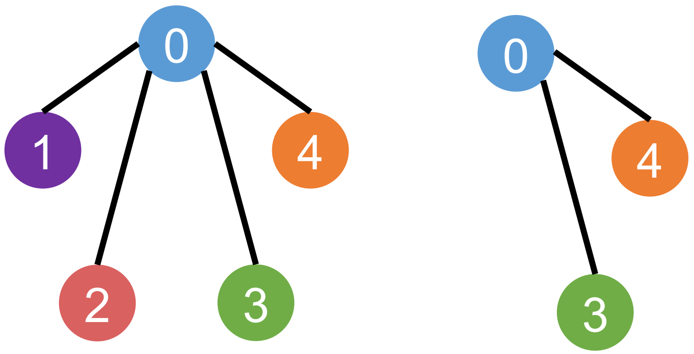

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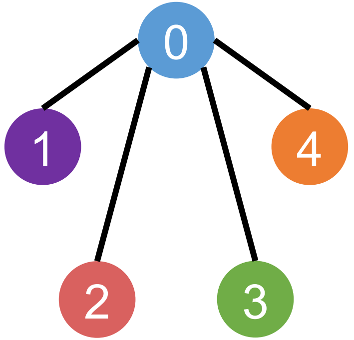

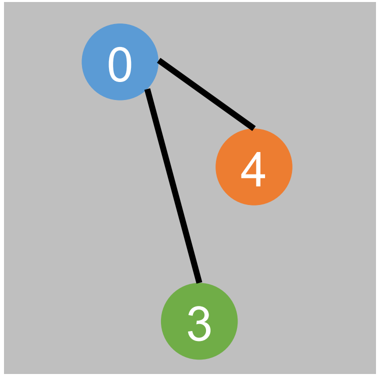

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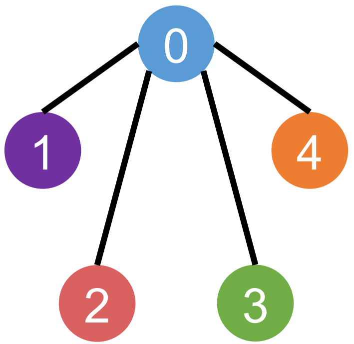

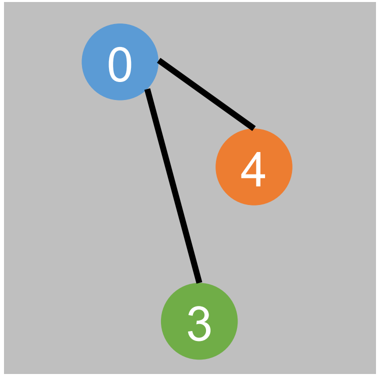

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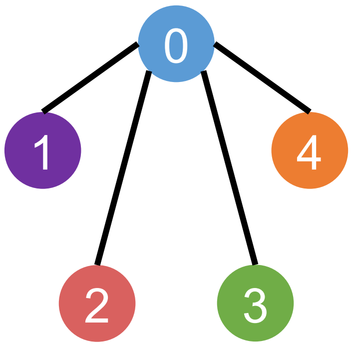

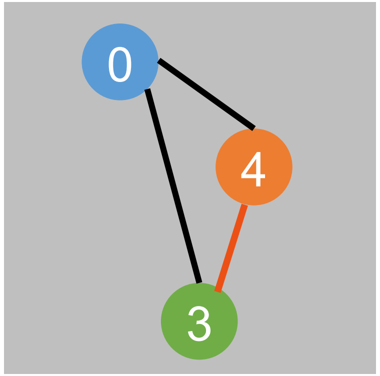

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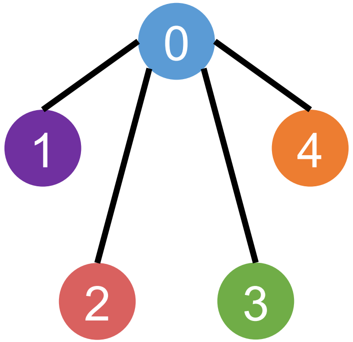

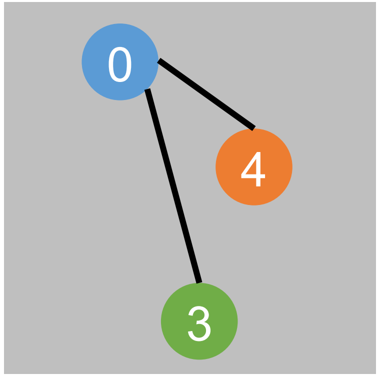

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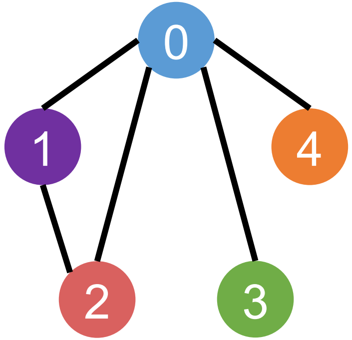

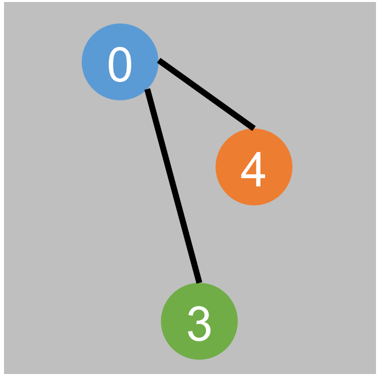

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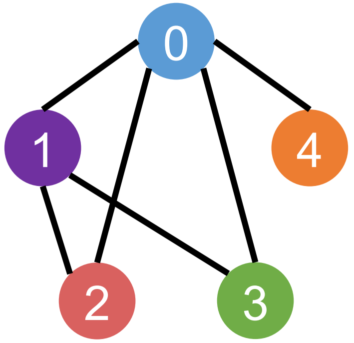

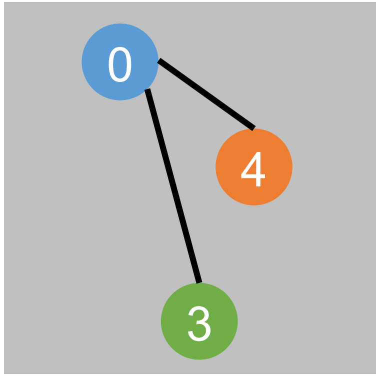

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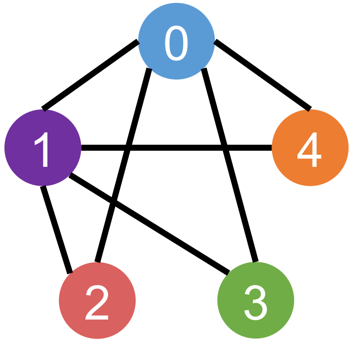
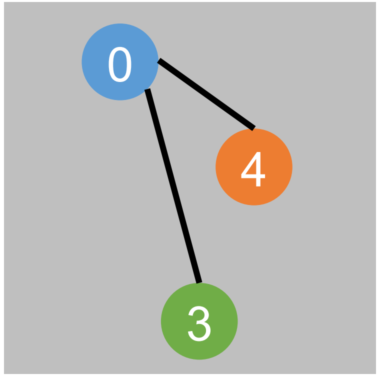
Using ASAP's API





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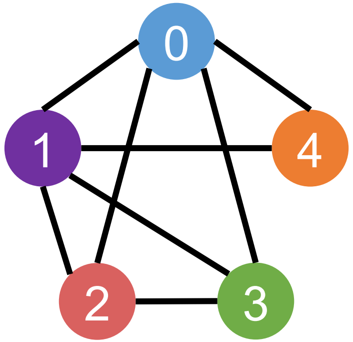

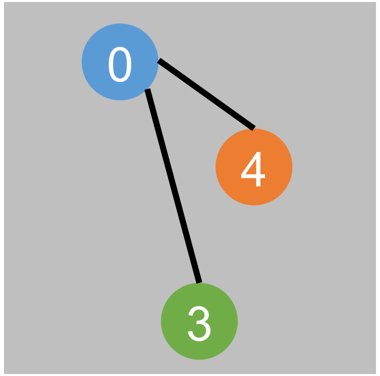

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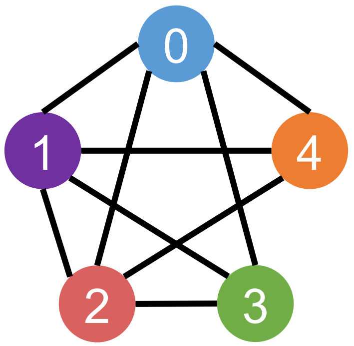

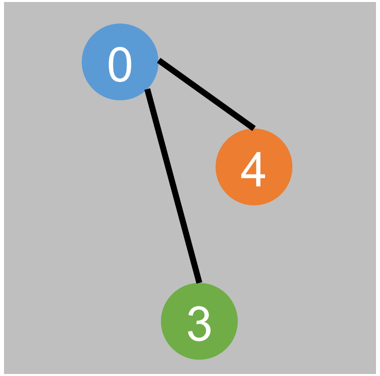

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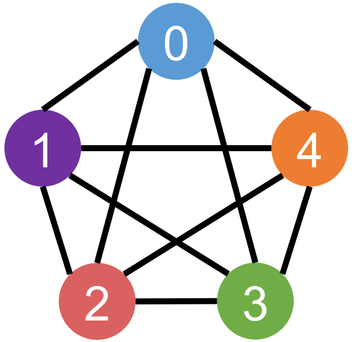

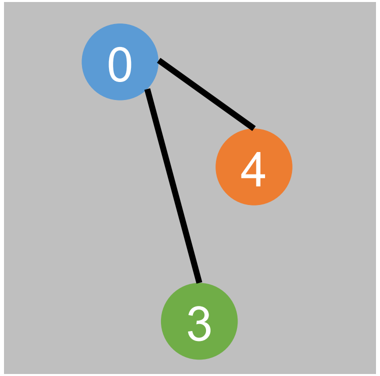

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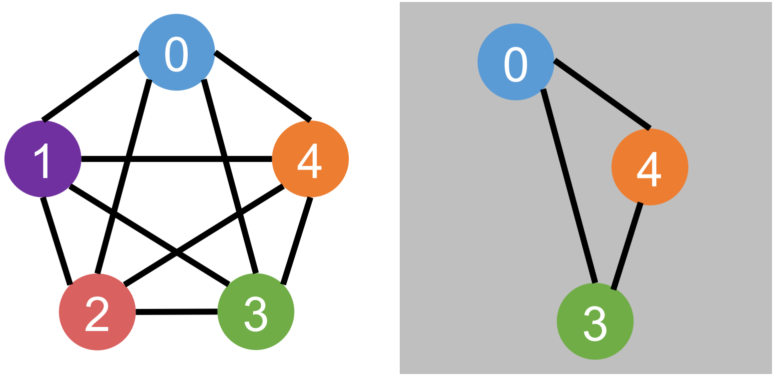

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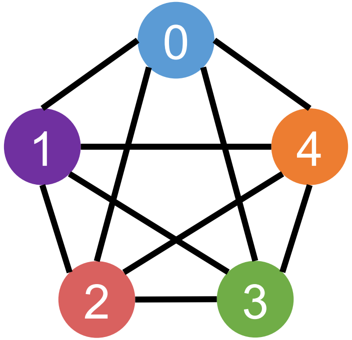

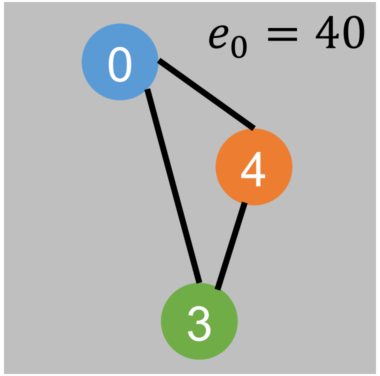

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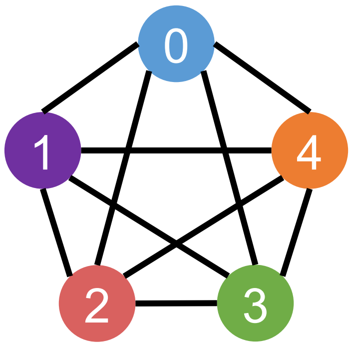

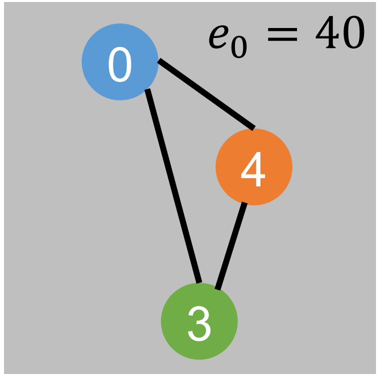

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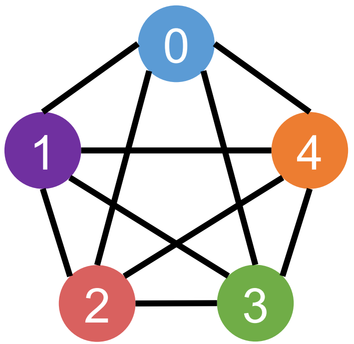
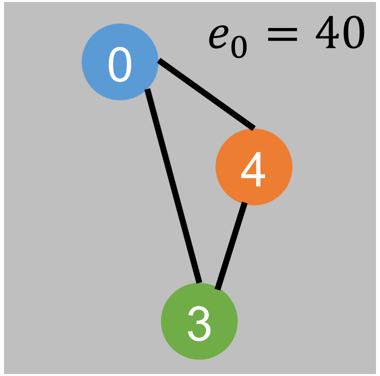
Sampling phase *fixes the vertices* for a particular instance of a pattern and closing phase *waits for remaining edges*

edge stream: (0,1), (0,2), (0,3), (0,4), (1,2), (1,3), (1,4), (2,3), (2,4), (3,4)

Using ASAP's API





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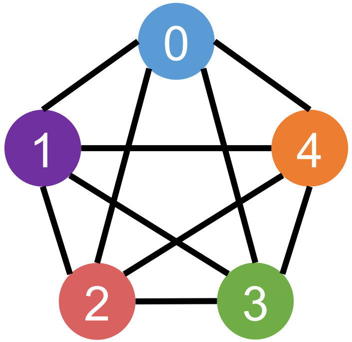
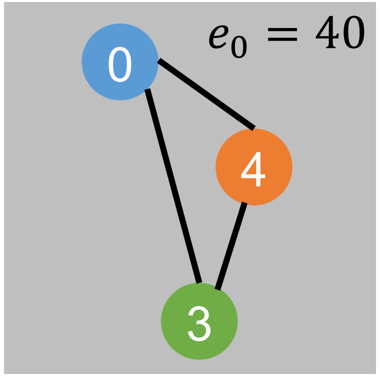
ASAP computes the right expectations, runs many instances of the estimator and aggregates results

Using ASAP's API

See paper for more examples & proof





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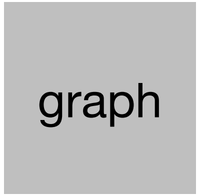
Applying to Distributed Settings



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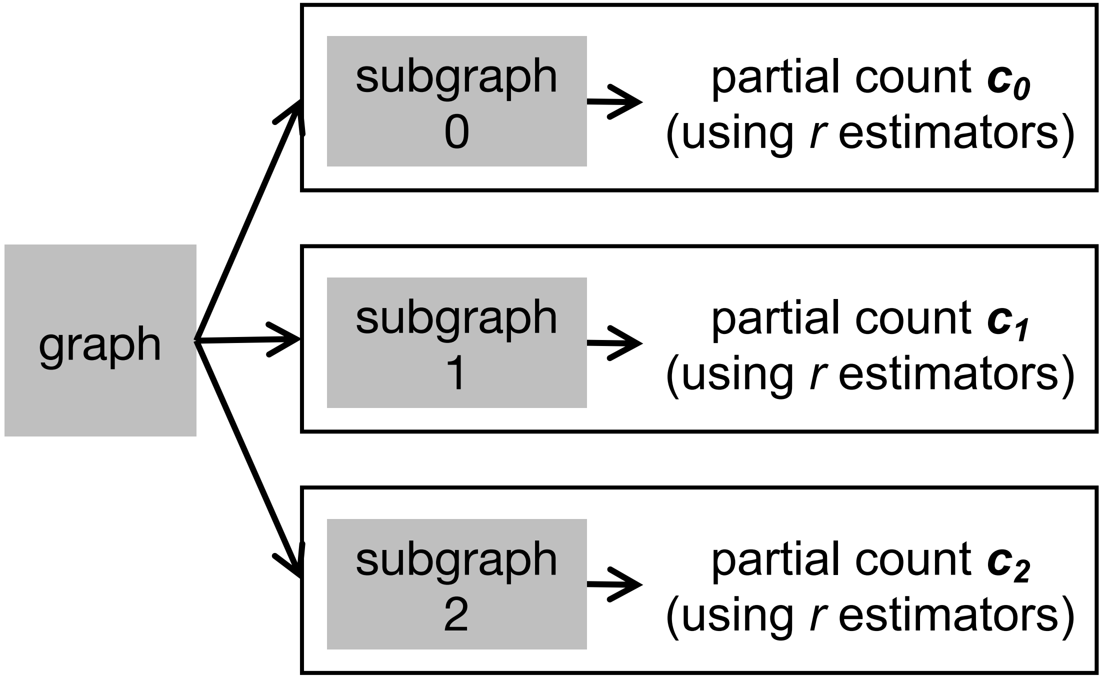

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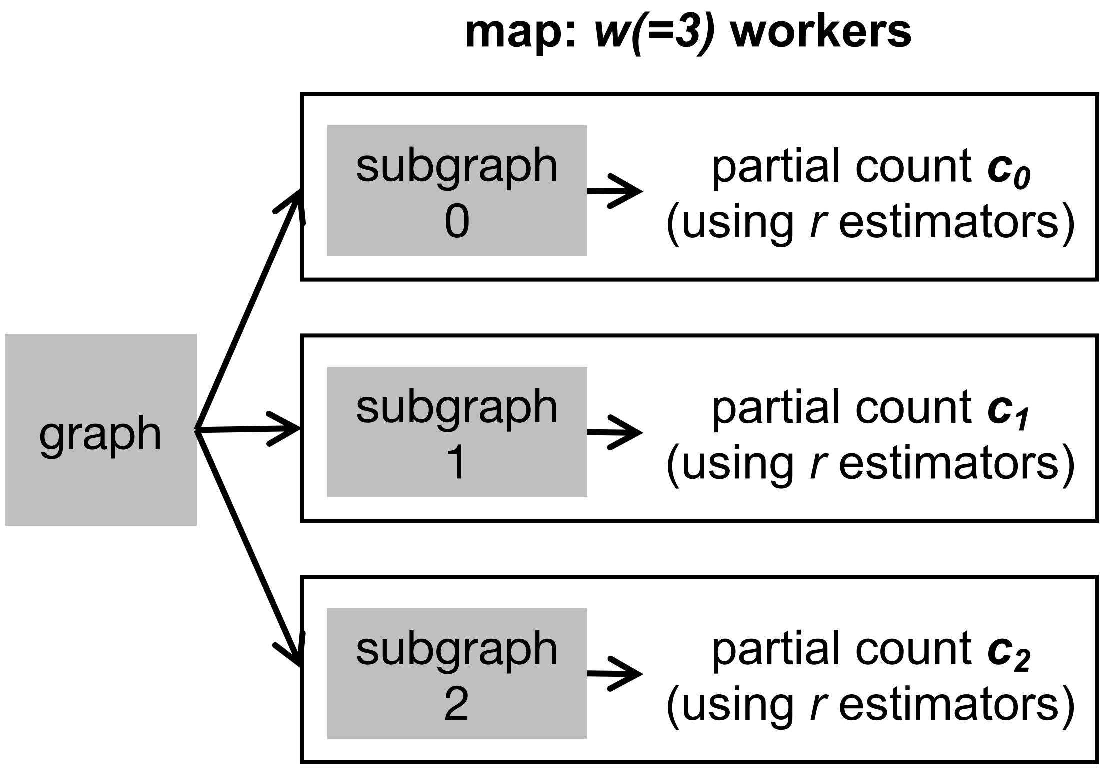

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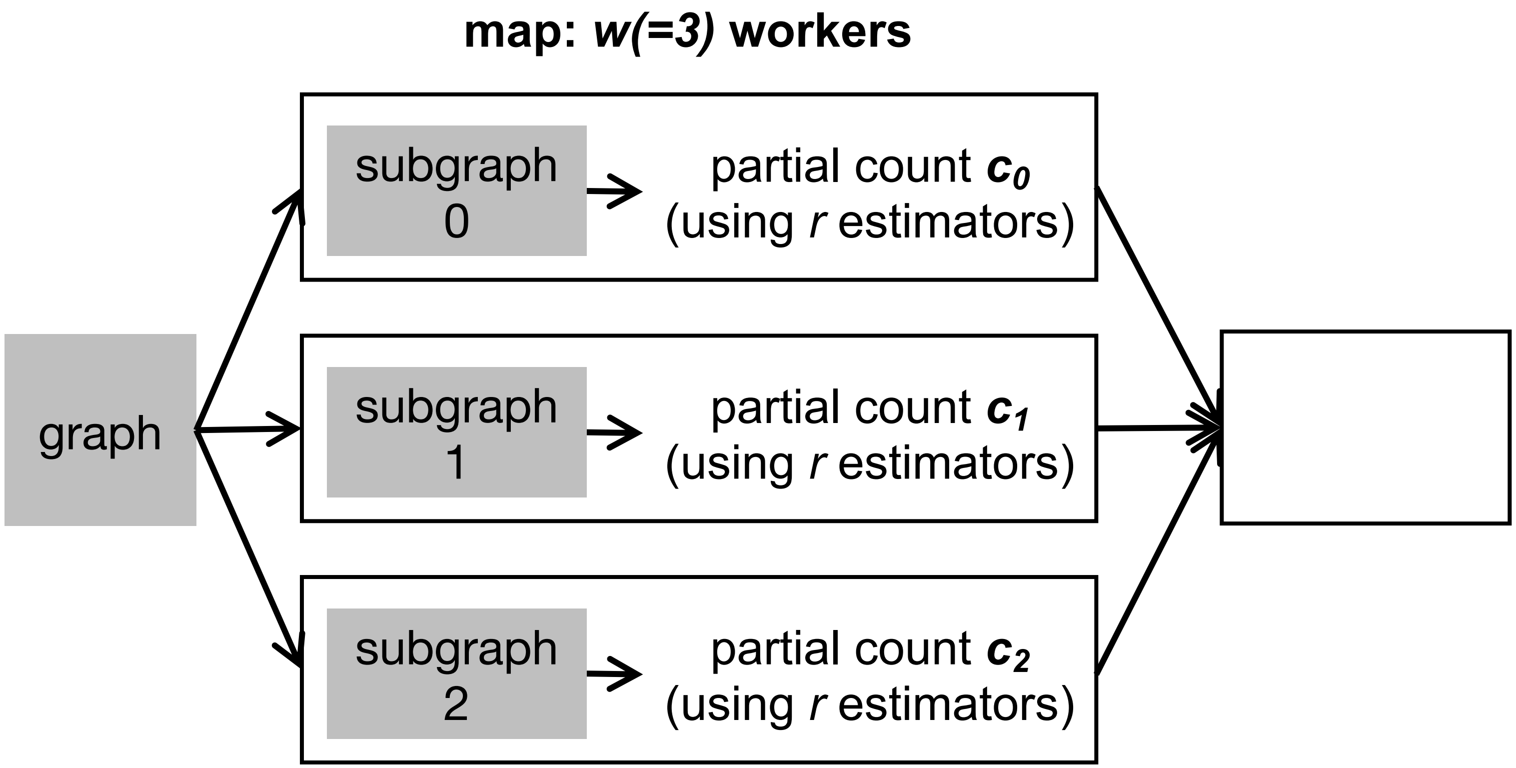

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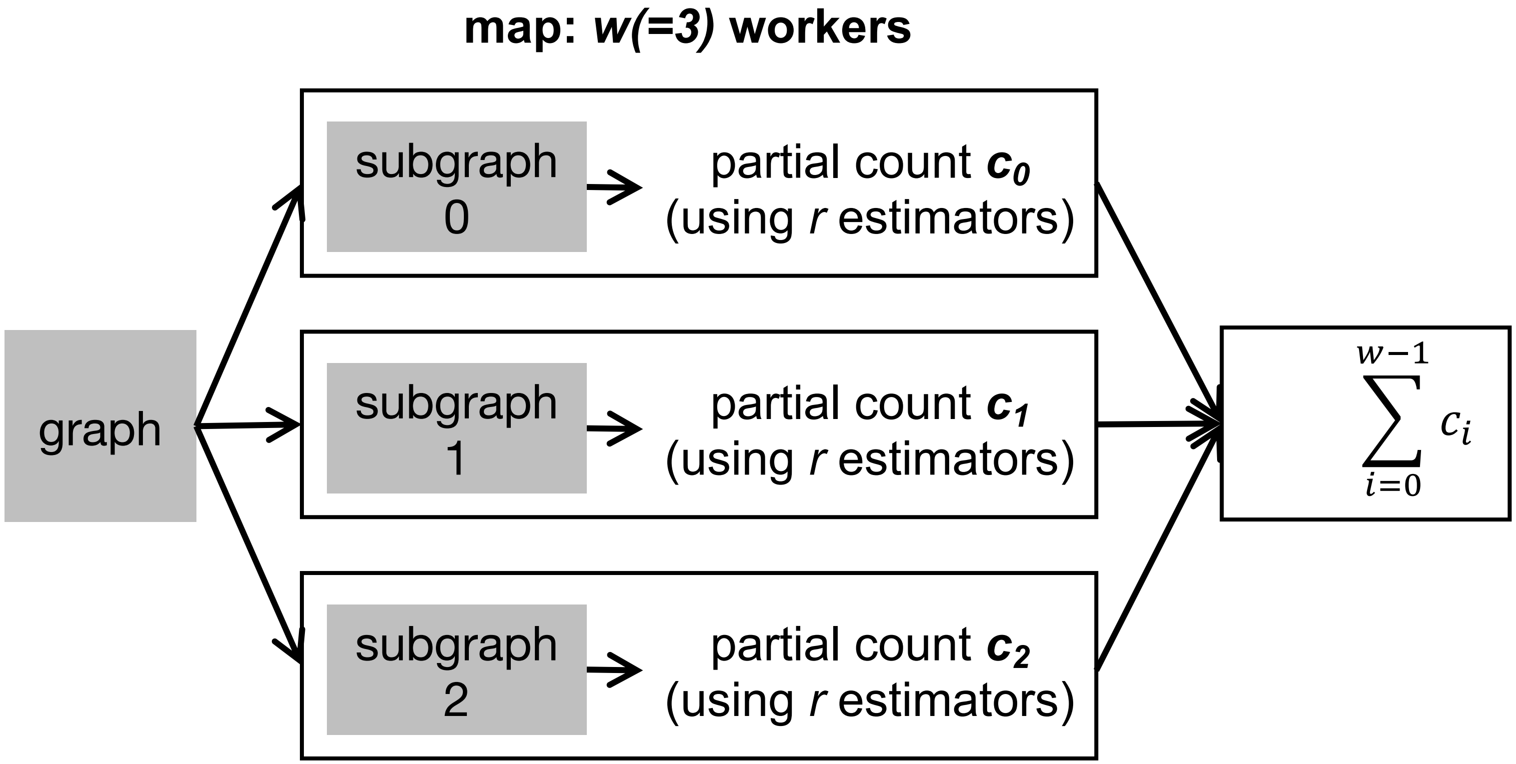

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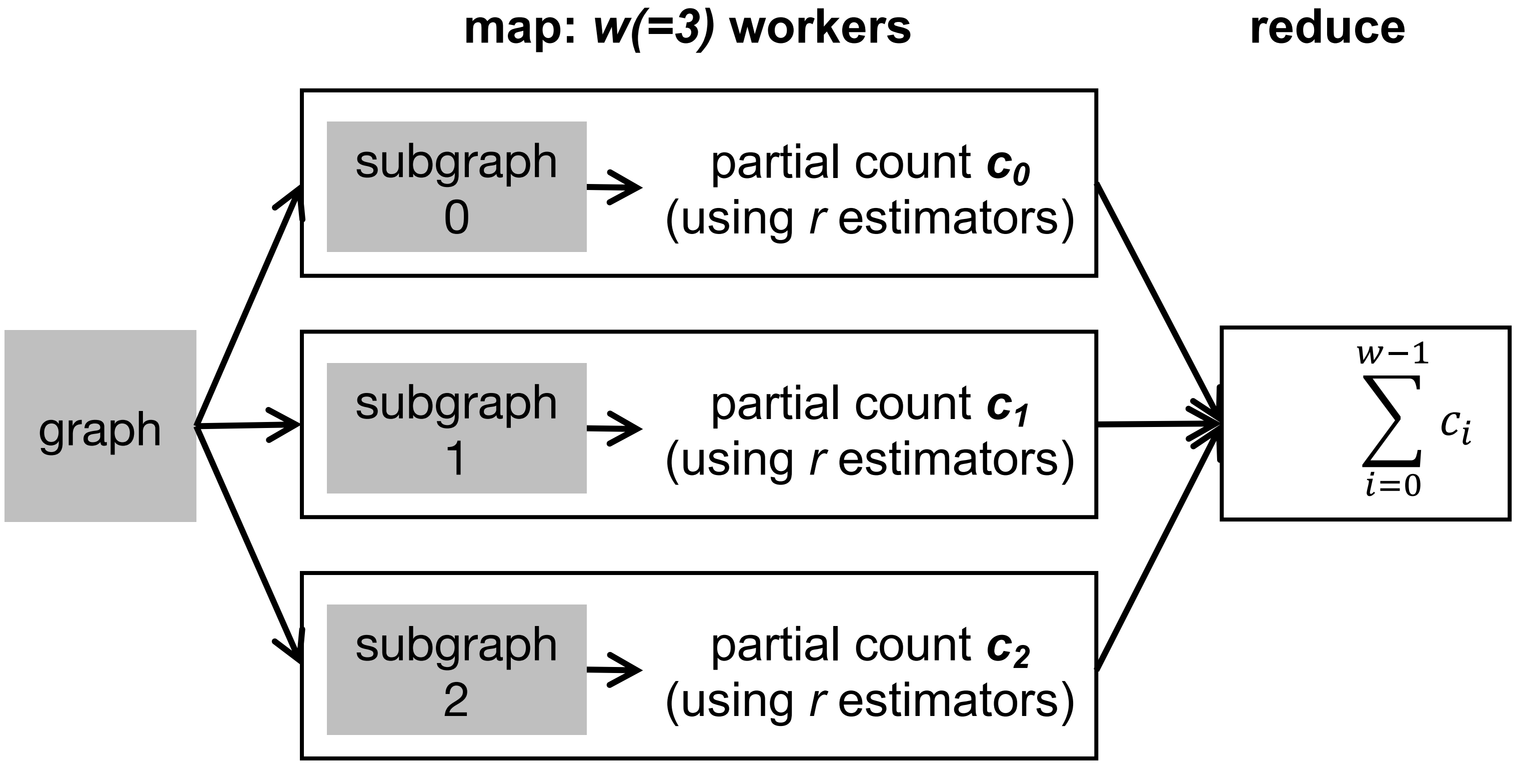

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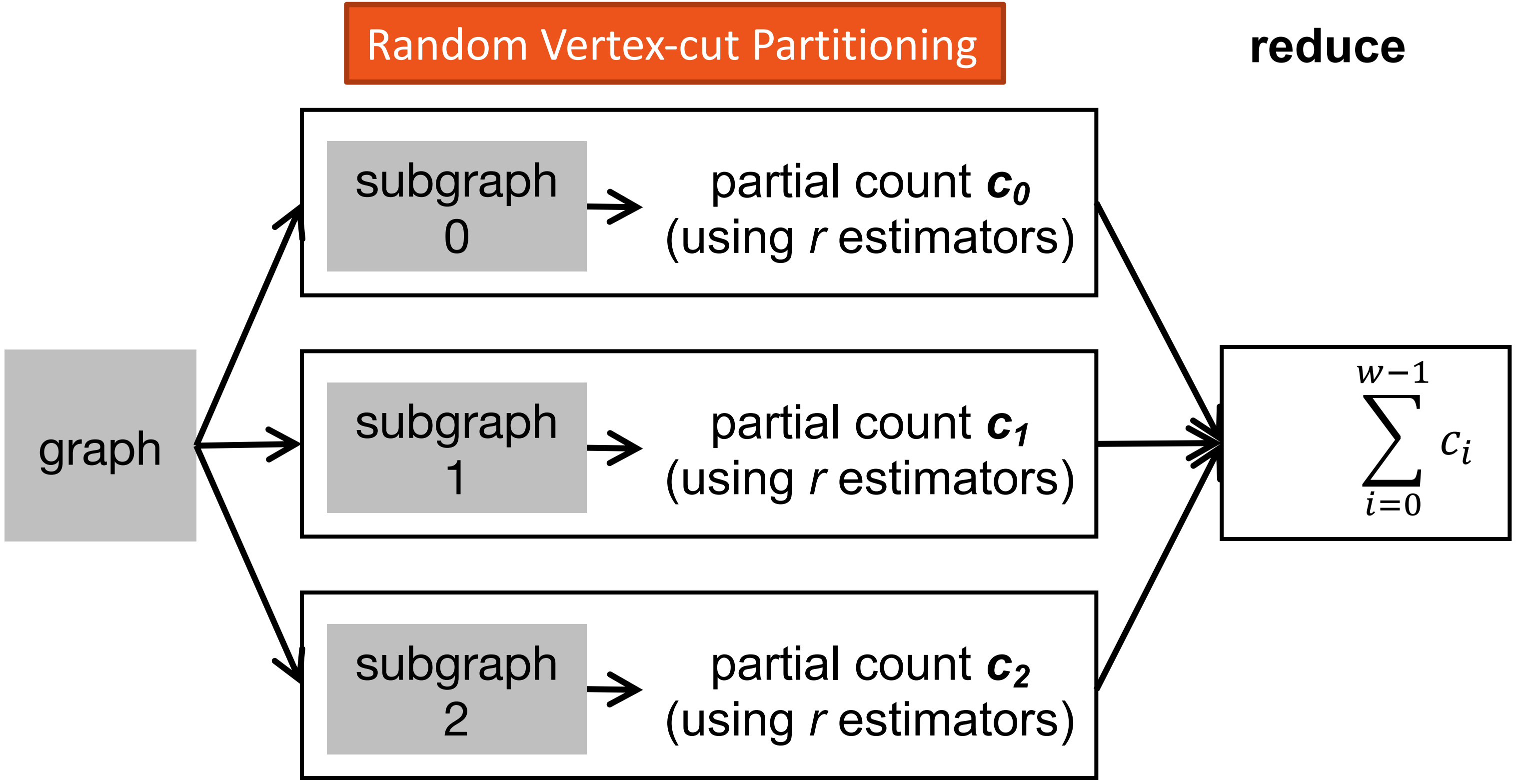

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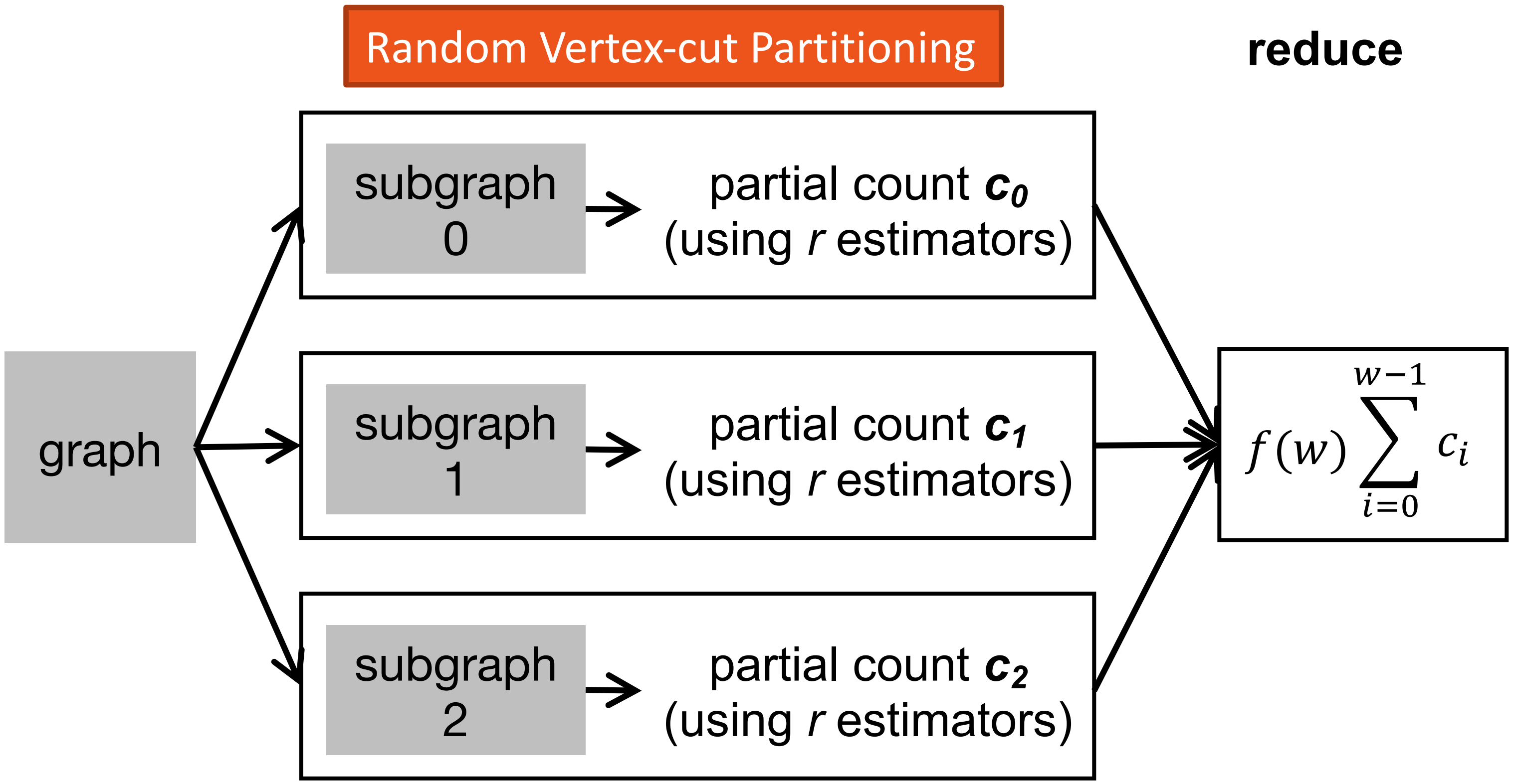

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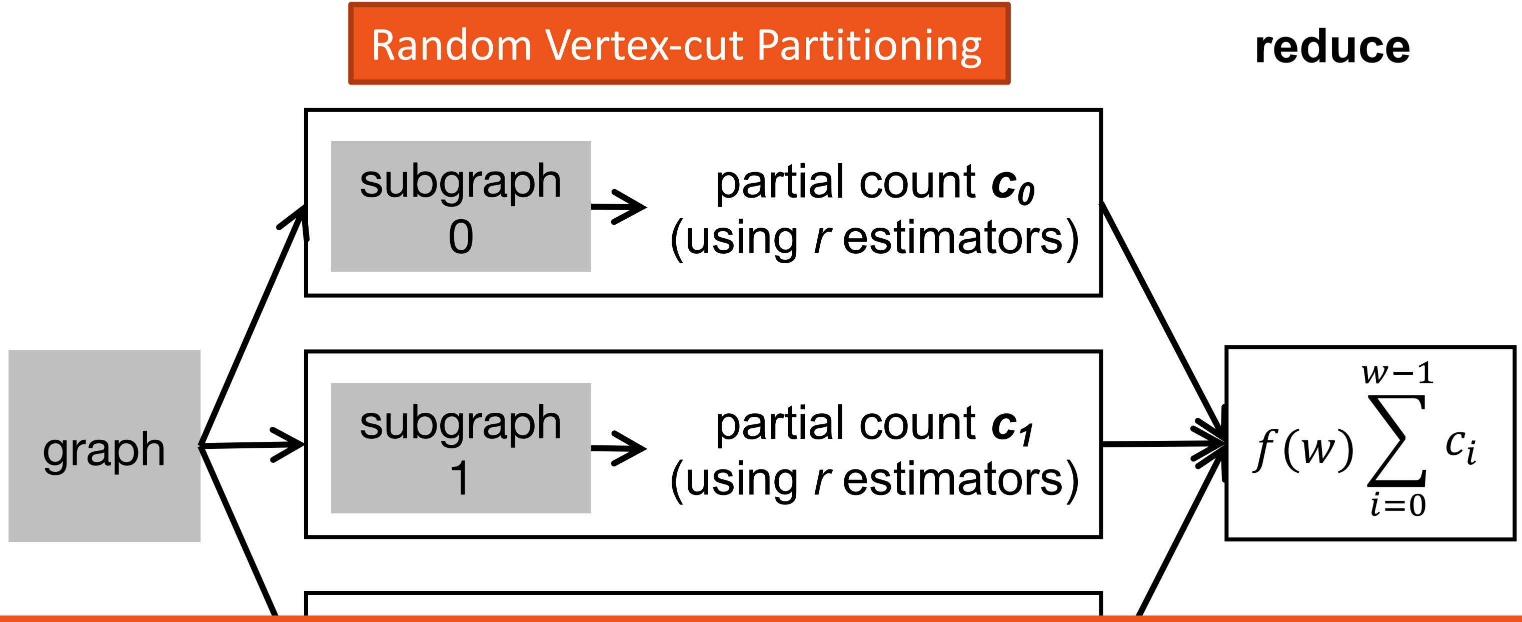
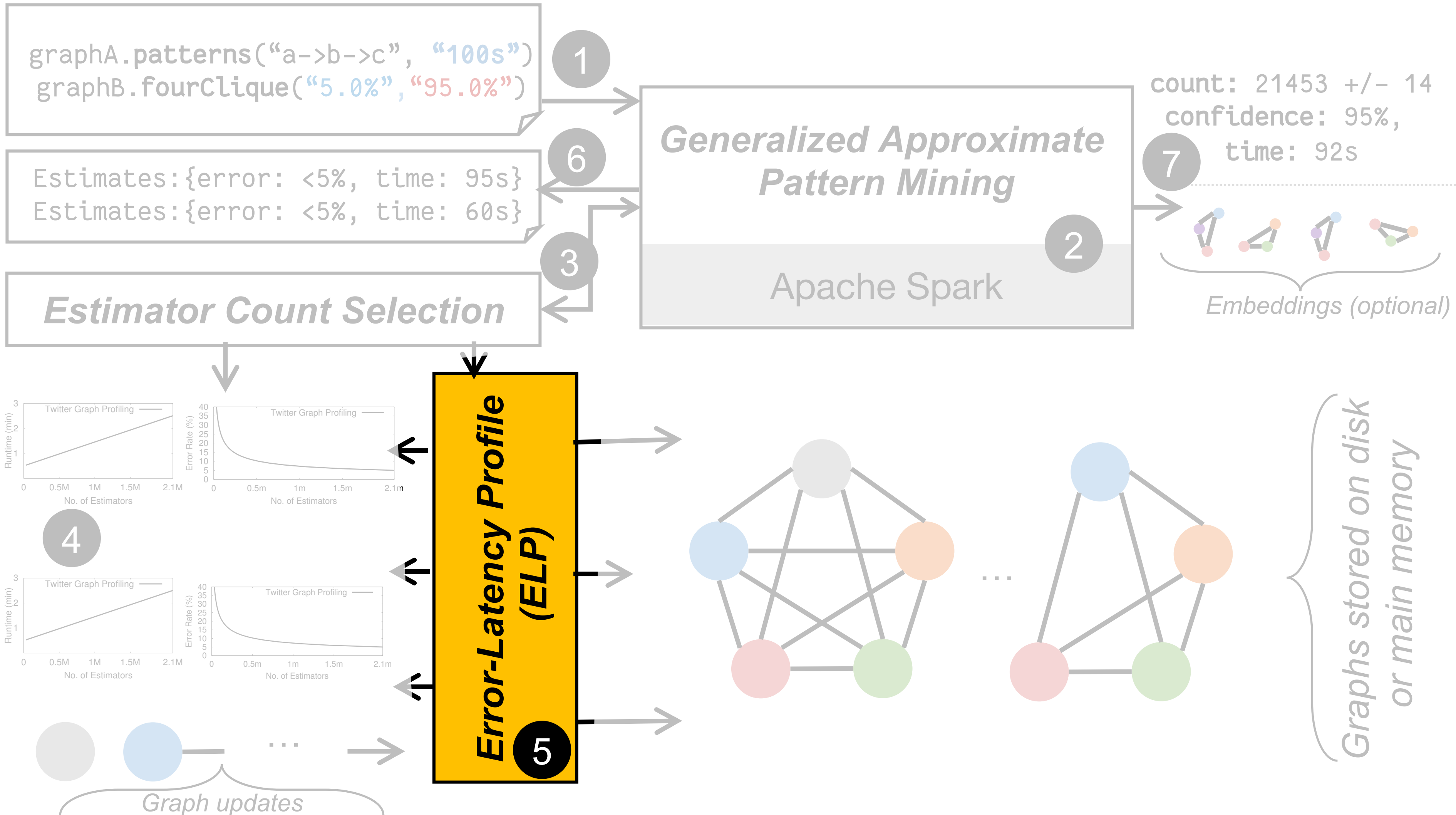


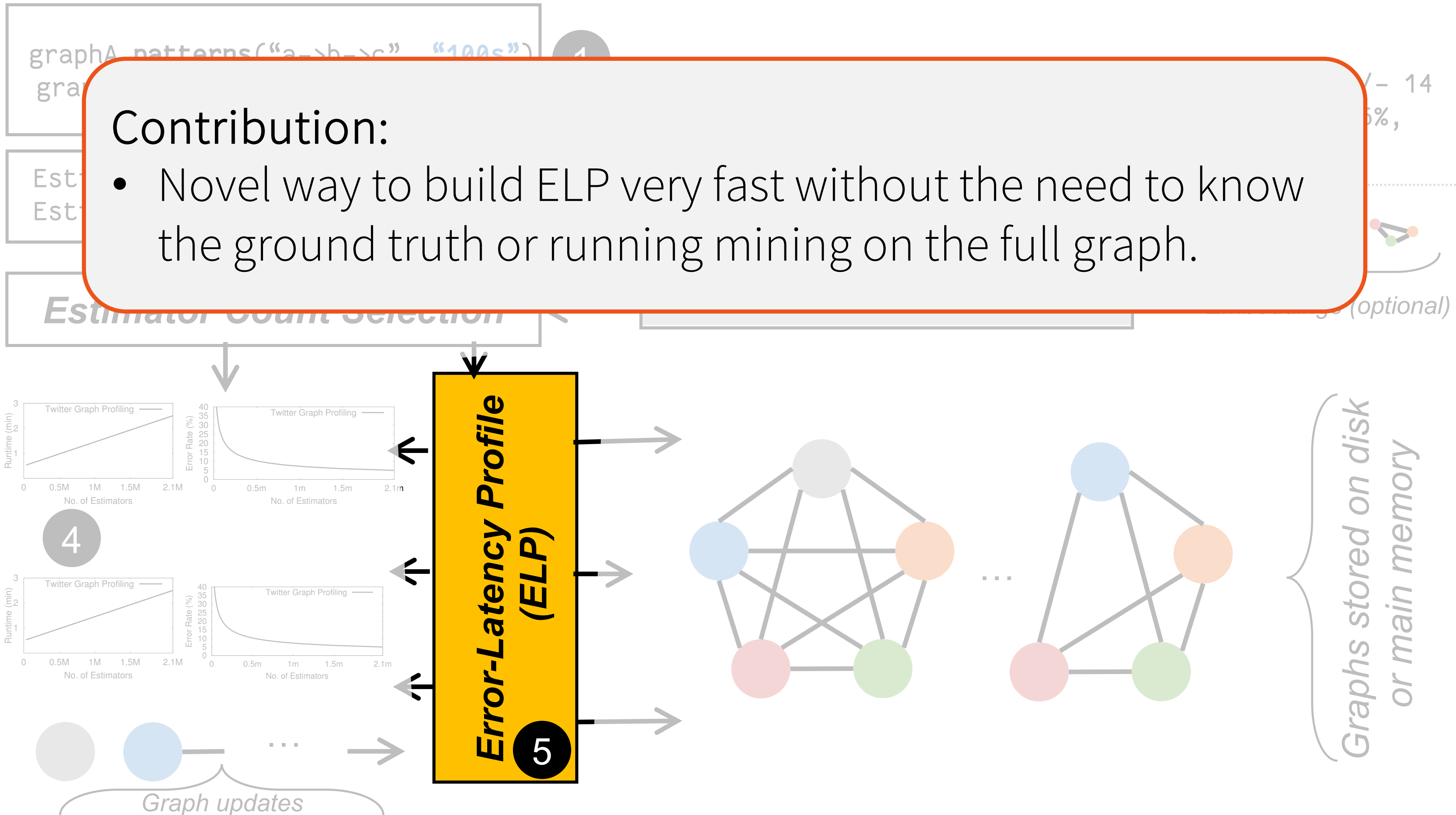
Upper bounds on f(w) can be proved using Hajnal-Szemerédi theorem



graphA.patterns("a->b->c", "100s")
graphB.fourClique("5.0%","95.0%")
1
Generalized Approximate Pattern Mining
Apache Spark
2
count: 21453 +/- 14
confidence: 95%,
time: 92s
7
Embeddings (optional)
6
Estimates:{error: <5%, time: 95s}
Estimates:{error: <5%, time: 60s}
3
Estimator Count Selection
Twitter Graph Profiling
Runtime (min)
No. of Estimators
Error Rate (%)
4
Error-Latency Profile (ELP)
5
Graphs stored on disk or main memory
Graph updates

Contribution:

- Novel way to build ELP very fast without the need to know the ground truth or running mining on the full graph.



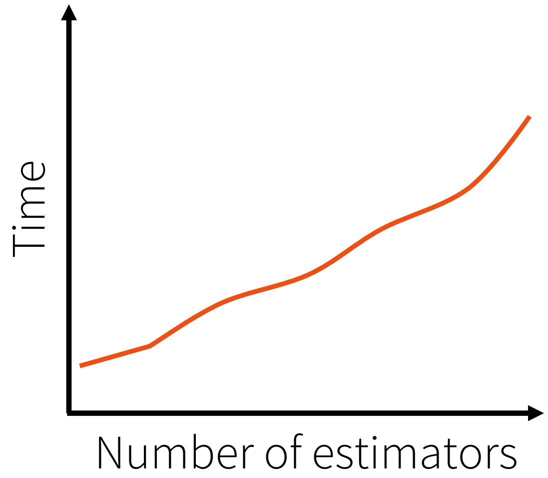
Building Error-Latency Profile

Given a time / error bound, how many estimators should ASAP use?

Building Error-Latency Profile

Given a time / error bound, how many estimators should ASAP use?

Time vs Estimators



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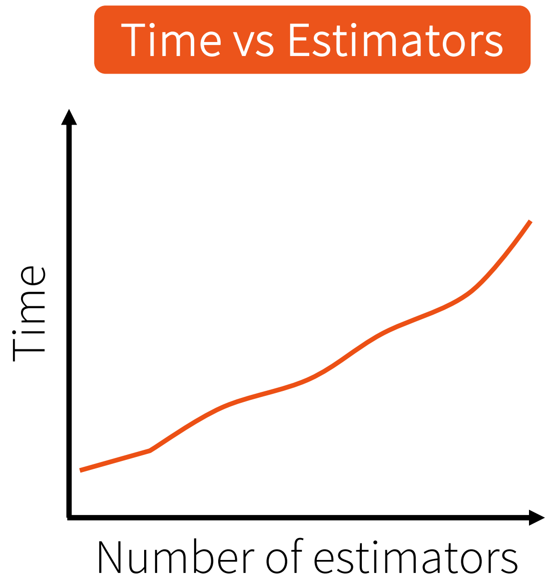

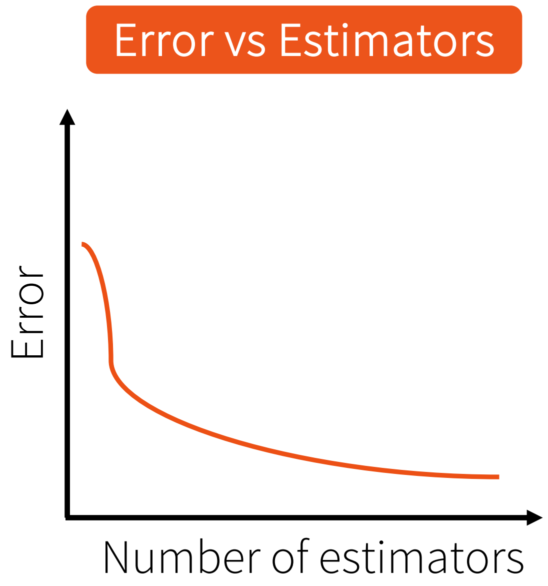

Building Estimators vs Time Profile

- Time complexity linear in number of estimators

Building Estimators vs Time Profile

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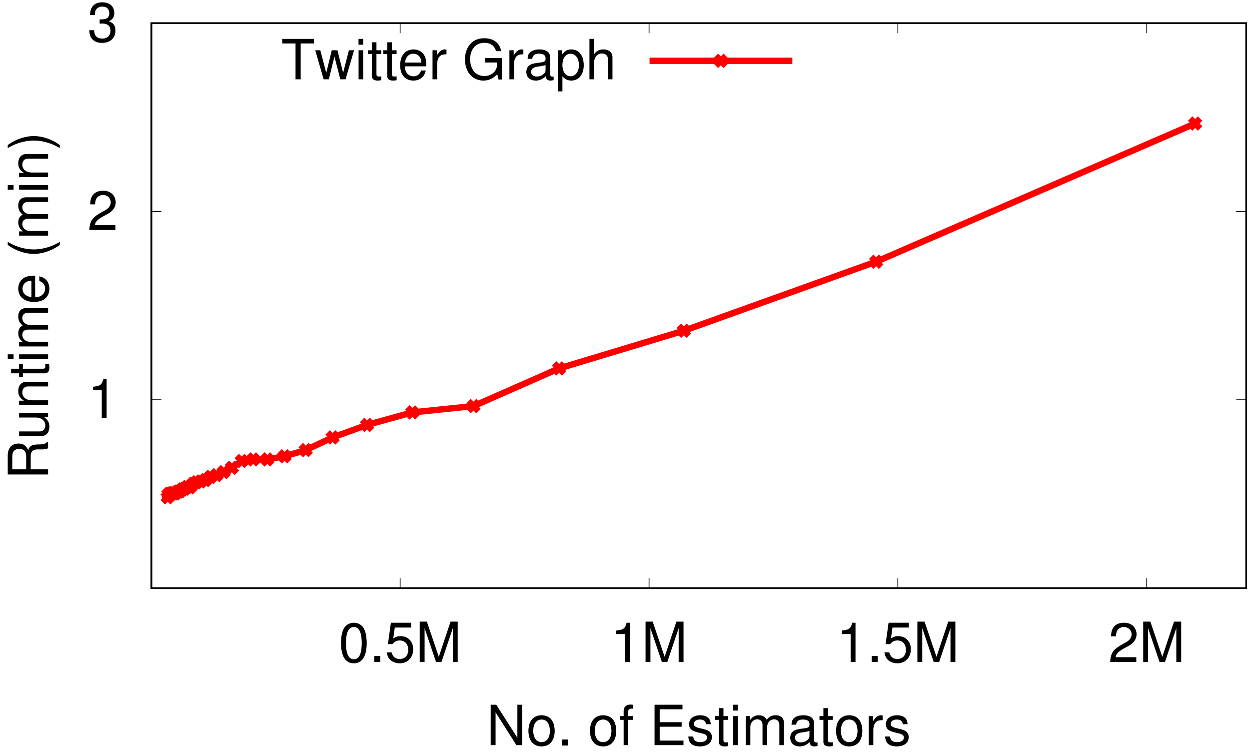

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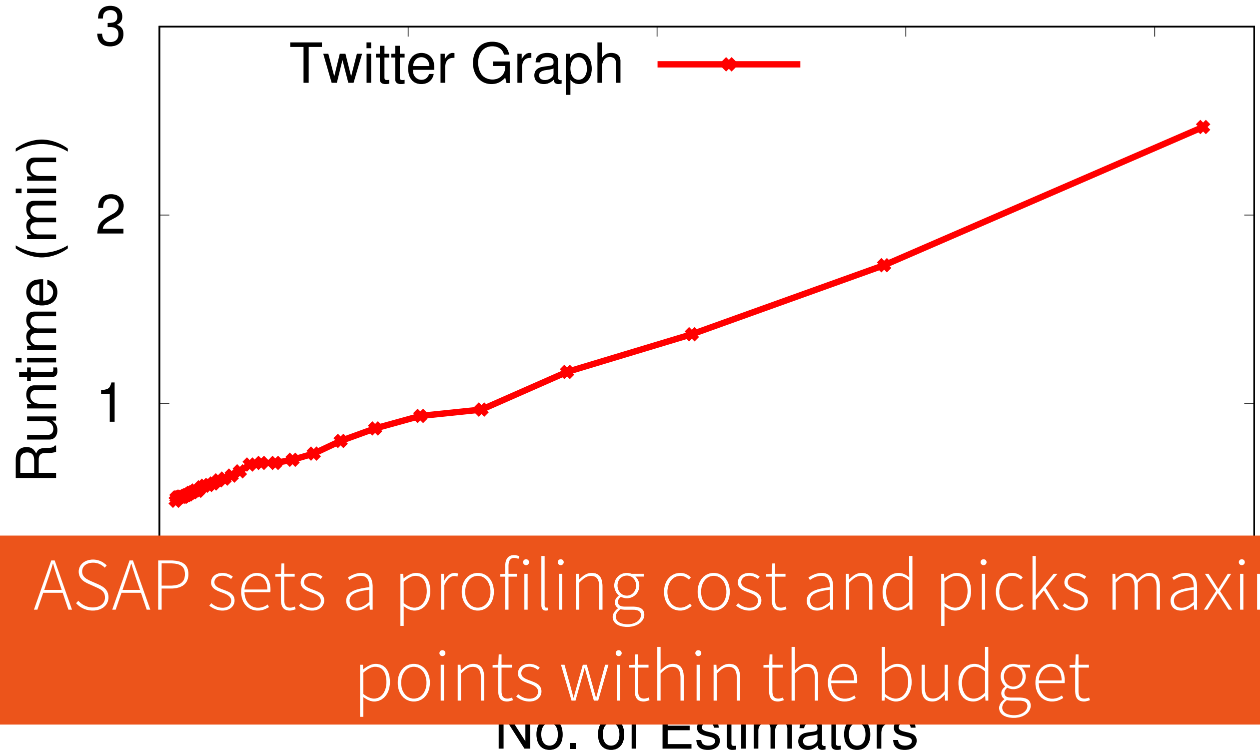
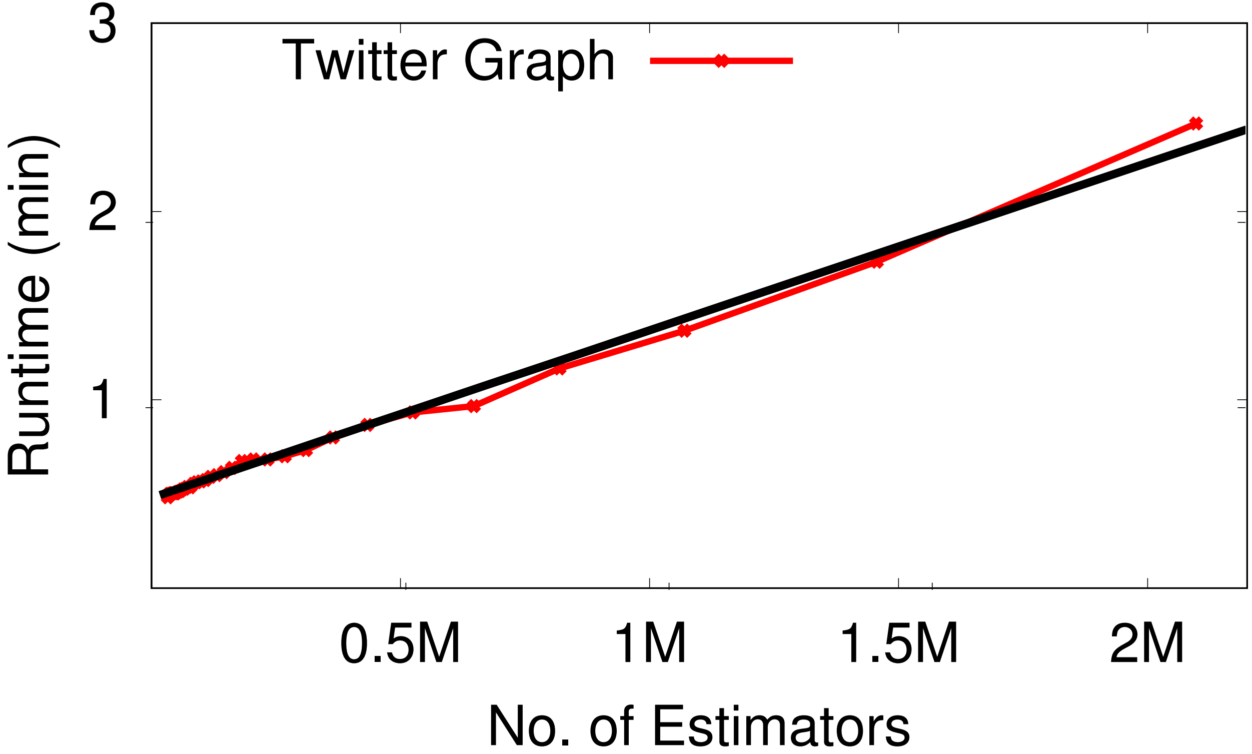


ASAP sets a profiling cost and picks maximum points within the budget

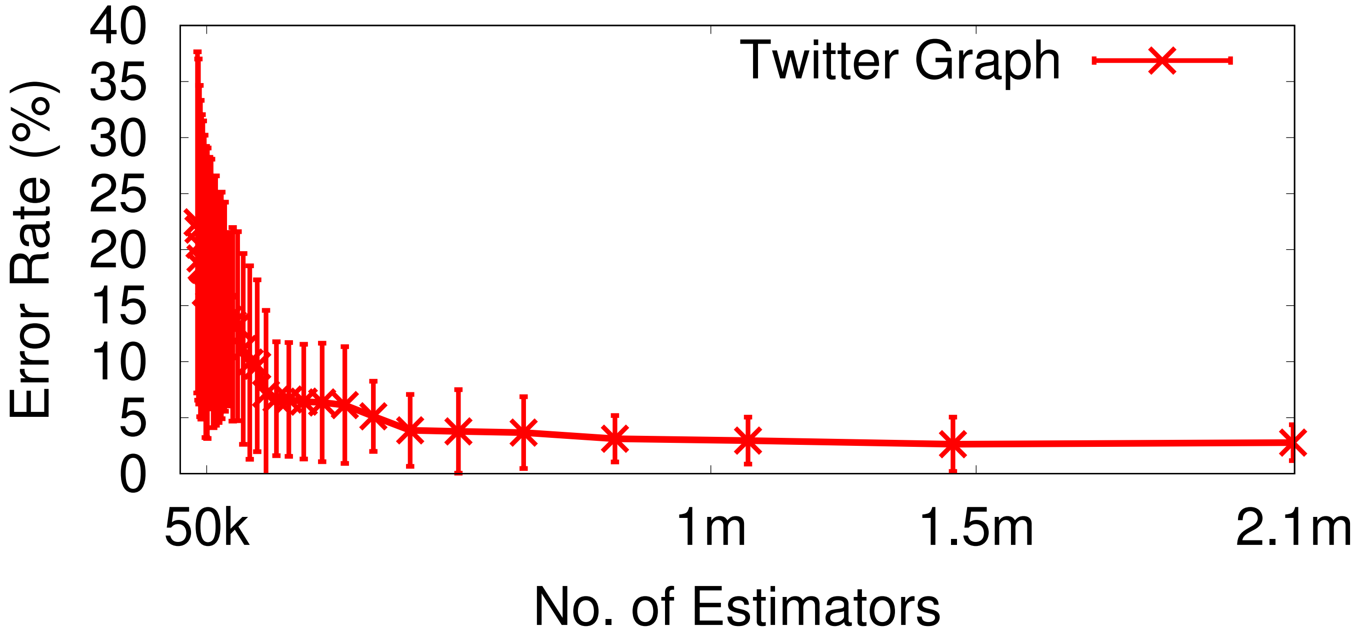
Building Estimators vs Time Profile

Time complexity linear in number of estimators



Building Estimators vs Error Profile

Error complexity non-linear in number of estimators



Building Estimators vs Error Profile

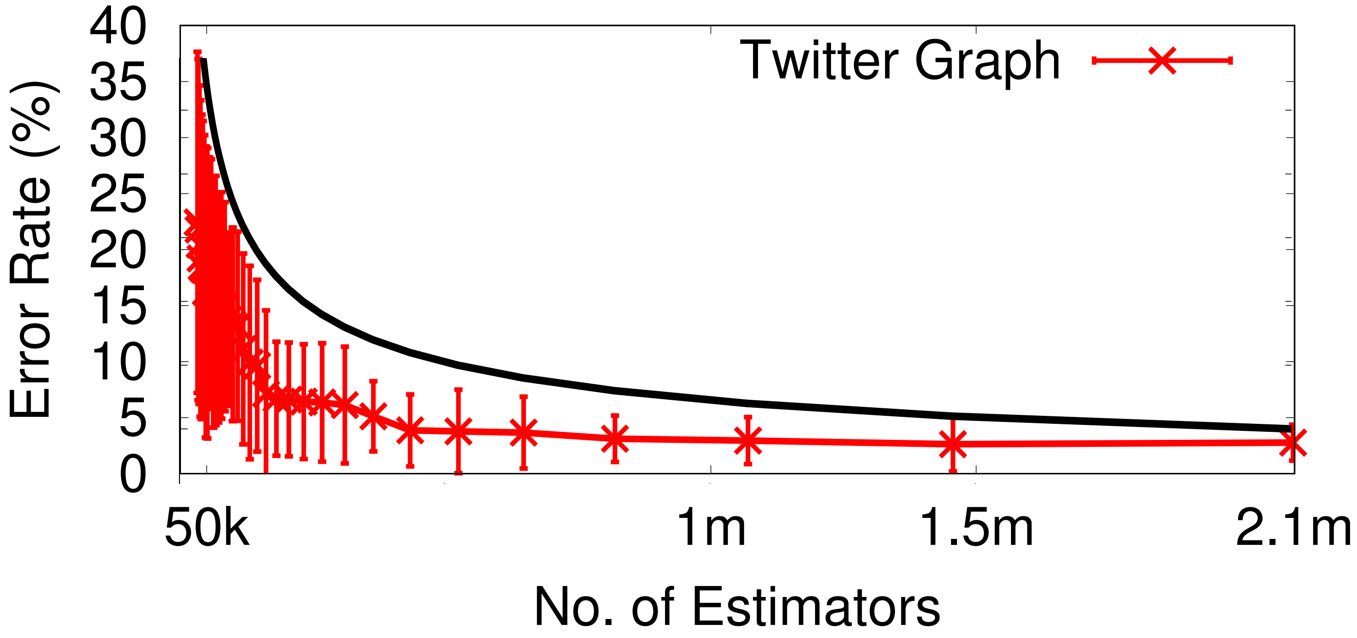
Error complexity non-linear in number of estimators

Key idea: Use a very small sample of the graph to build the ELP

- Chernoff analysis provides a *loose upper bound* on the number of estimators.
- In small graphs, a *large number of estimators* can get us very *close to ground truth*.

Building Estimators vs Error Profile

Error complexity non-linear in number of estimators



Advanced Mining

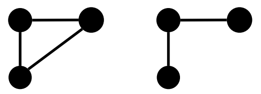
More details in the paper

Predicate Matching

- Find patterns where vertices are of type "electronics"
- ASAP allows simple edge and vertex predicates

Motif Mining

- Some patterns are building blocks for other patterns
- ASAP caches state of the estimators and reuses them



Accuracy Refinement

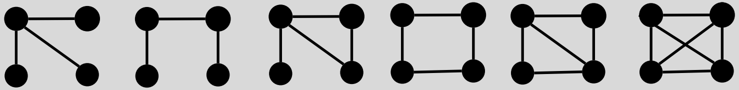
- Users may require more accurate answer later
- ASAP can checkpoint and reuse estimators

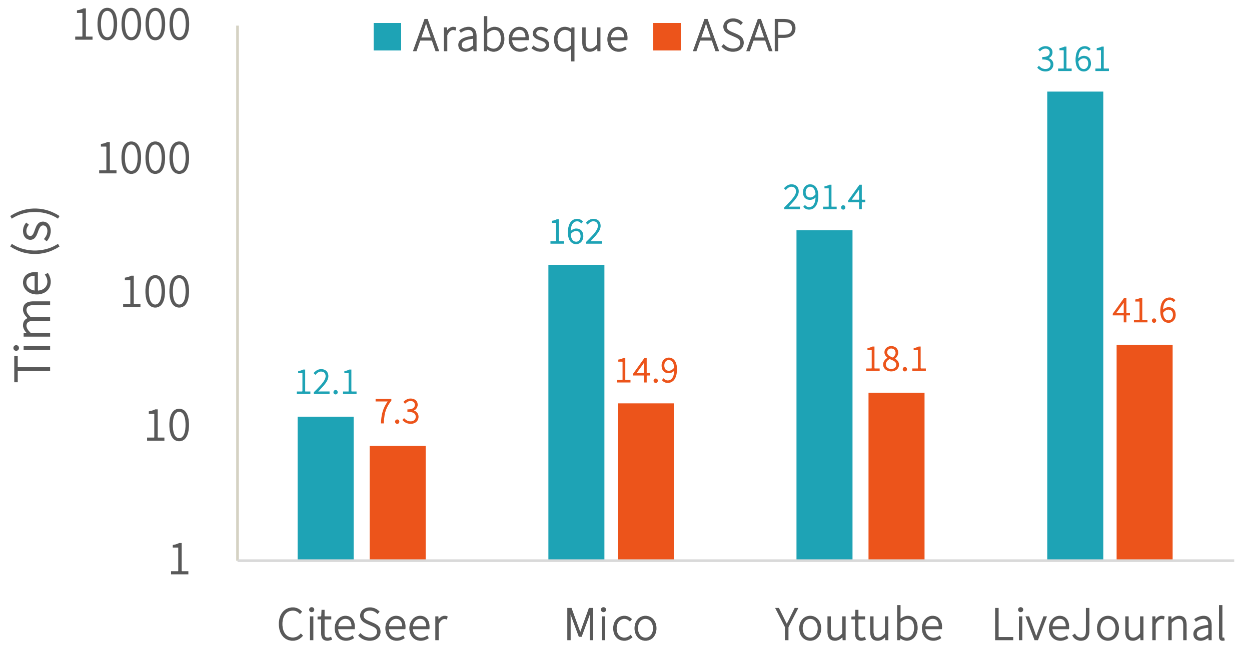
Implementation & Evaluation

- Implemented on Apache Spark
  - Not limited to it, only relies on simple dataflow operators
- Evaluated in a 16 node cluster
  - **Twitter:** 1.47B edges
  - **Friendster:** 1.8B edges
  - **UK:** 3.73B edges
- Comparison using representative patterns:
  - 3 (2 patterns), 4 (6 patterns) and 5 motifs (21 patterns)

Performance on Small Graphs

4-Motifs (6 patterns)





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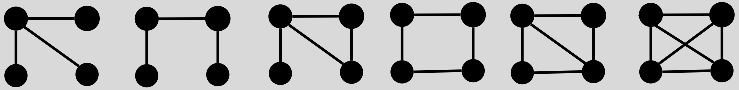

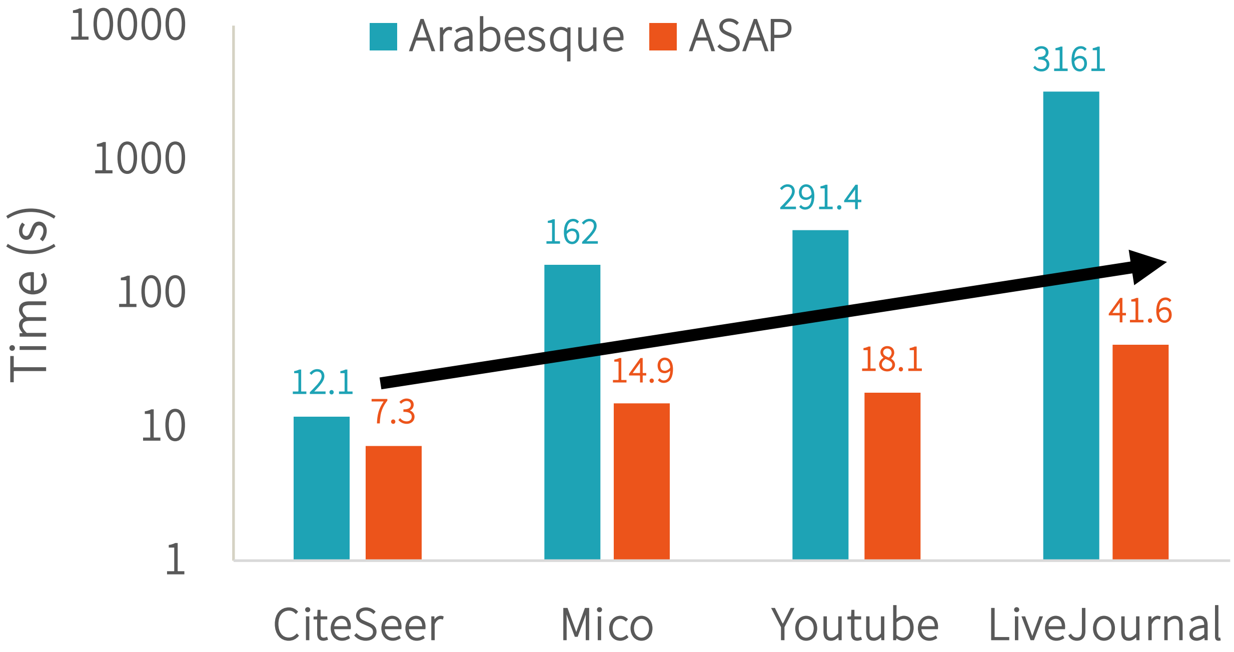

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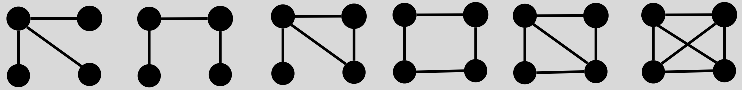
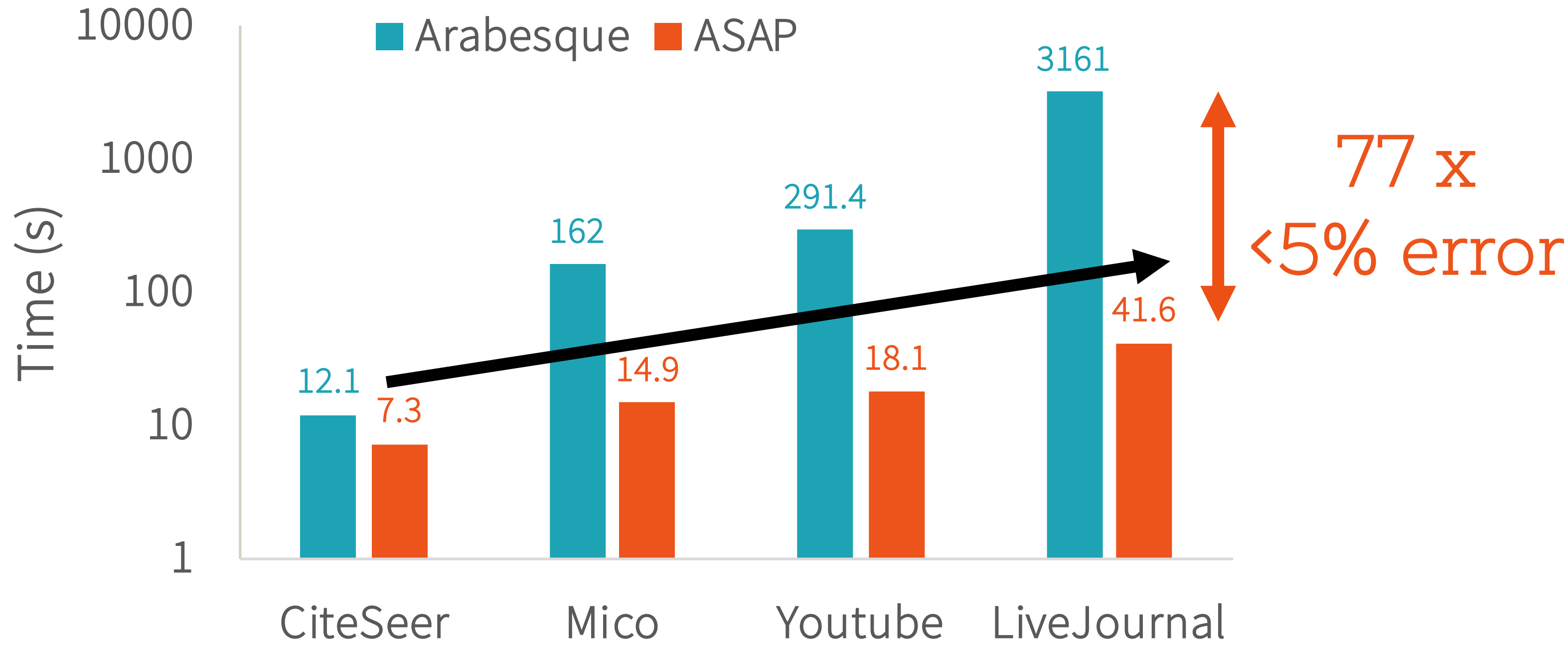
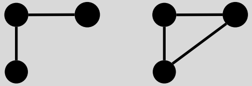
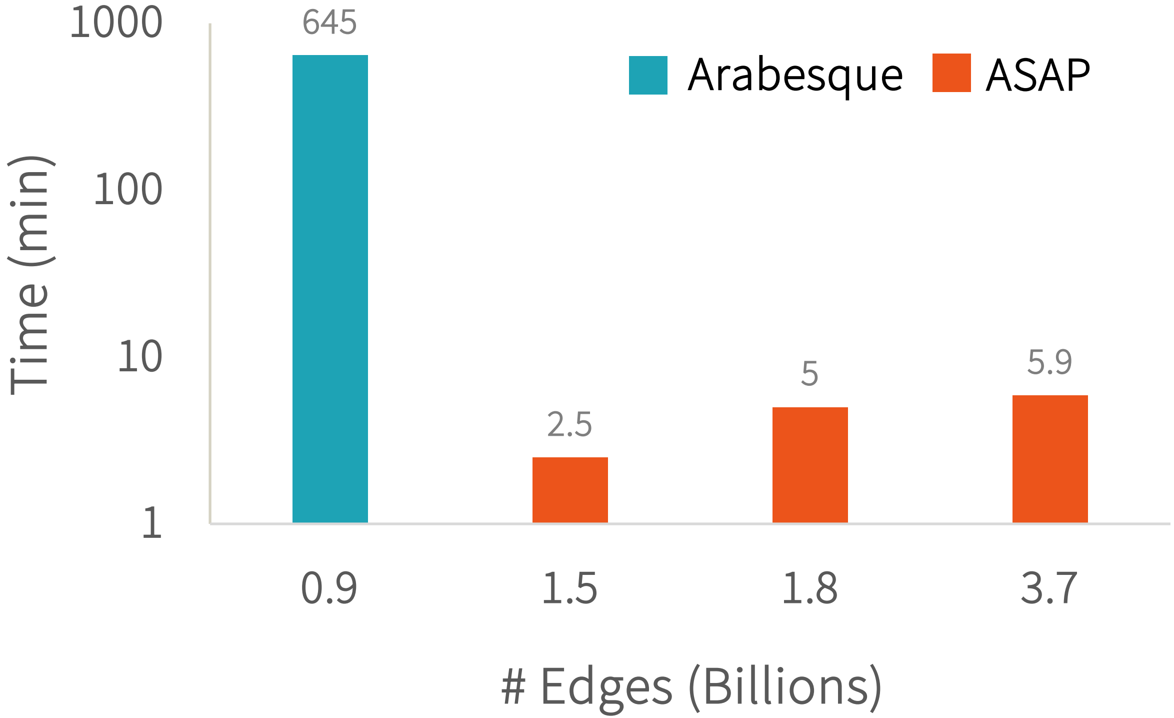
4-Motifs (6 patterns) 



Large Graphs & Simple Patterns

3-Motifs (2 patterns) 



Large Graphs & Simple Patterns

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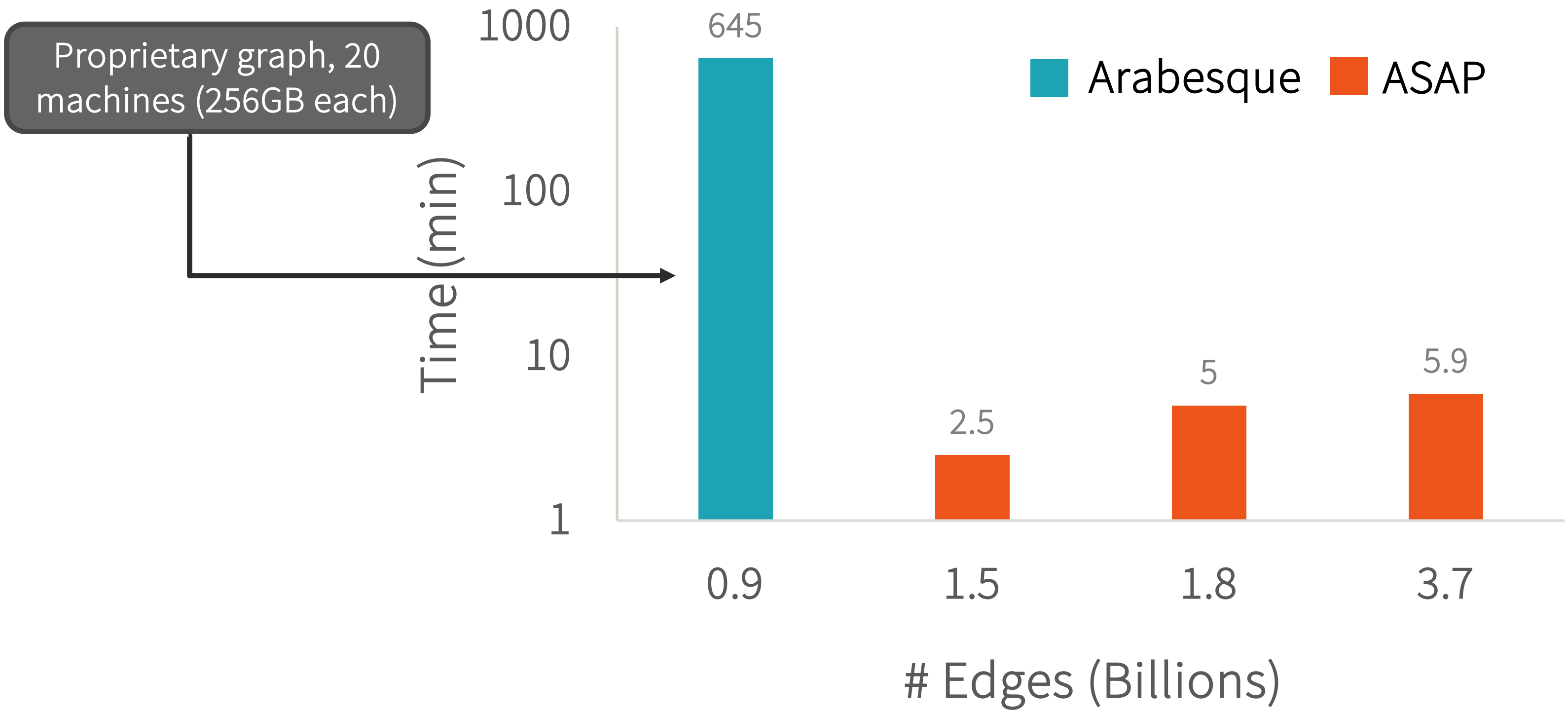

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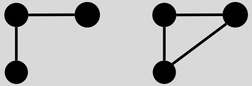
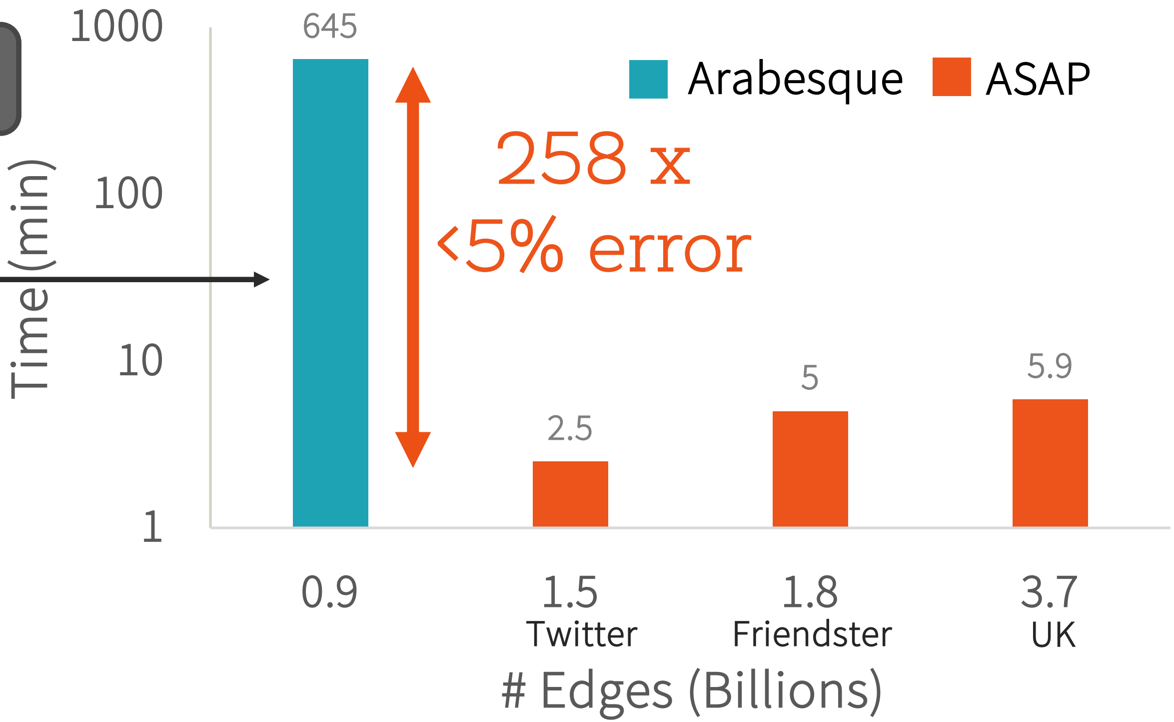


Proprietary graph, 20 machines (256GB each)



Large Graphs & Simple Patterns

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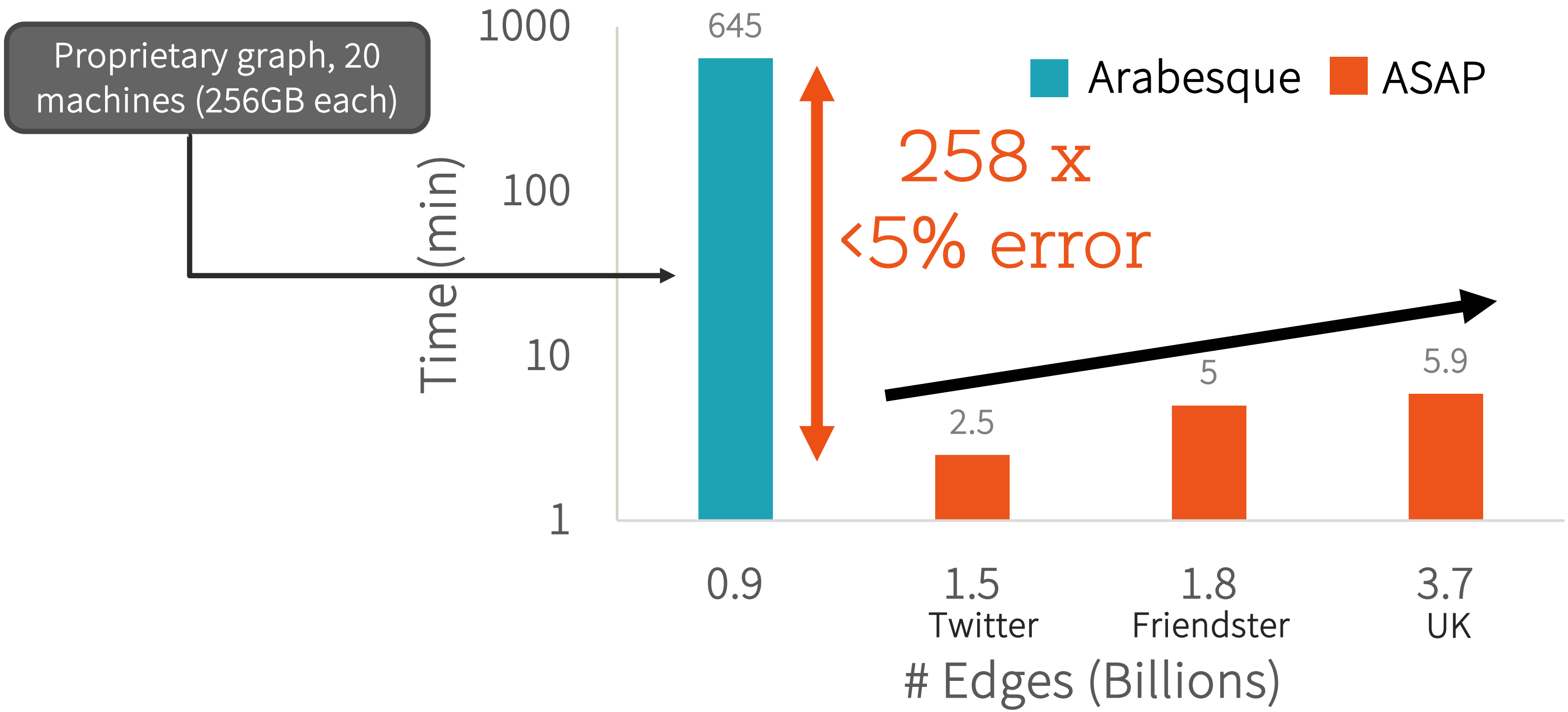
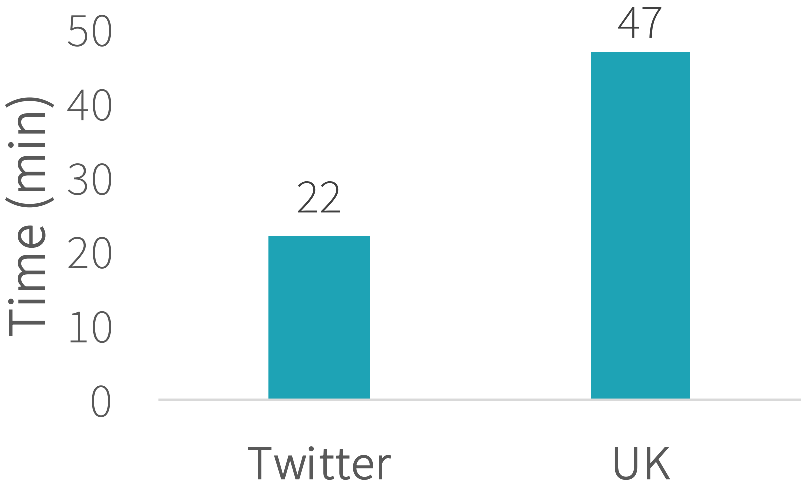
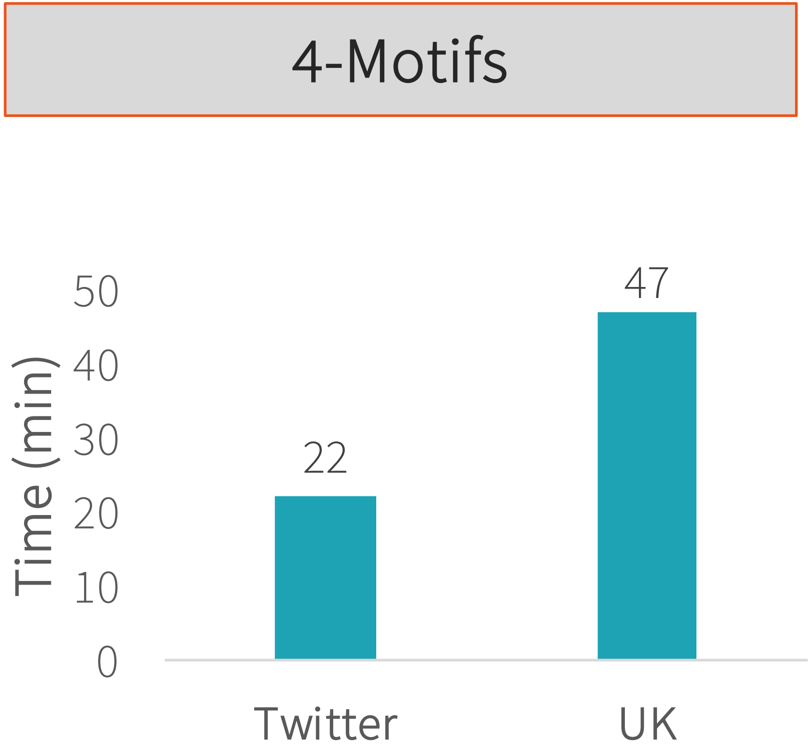


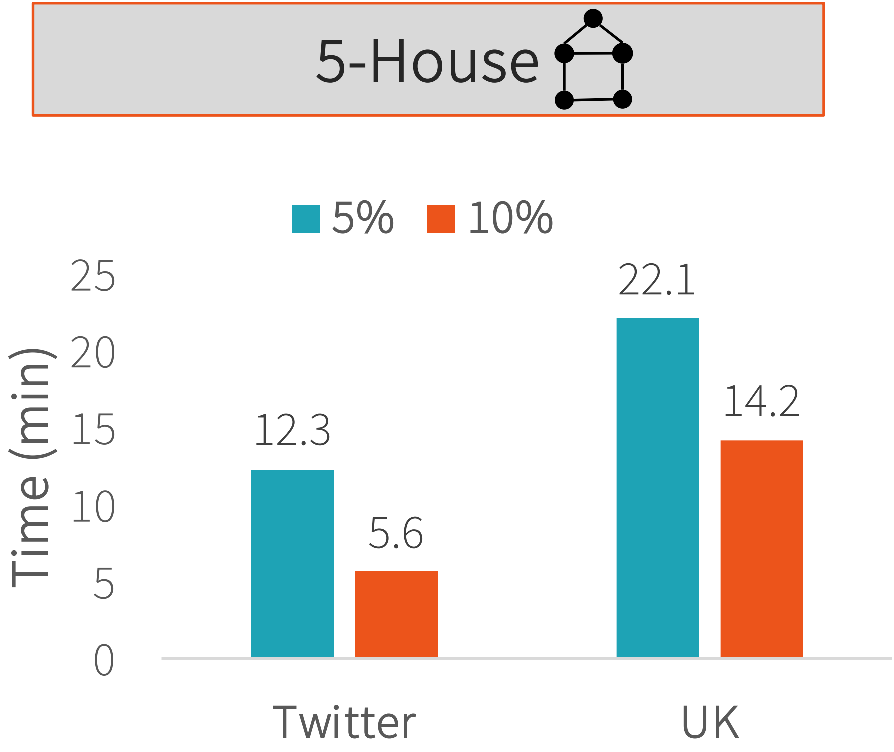
Large Graphs & Complex Patterns

4-Motifs



Large Graphs & Complex Patterns





Summary

- Pattern mining important & challenging problem
  - Applications in many domains
- ASAP uses approximation for fast pattern mining
  - Leverages graph mining theory & makes it practical
  - Simple API for developers
- ASAP outperforms existing solutions
  - Can handle much larger graphs with fewer resources

http://www.cs.berkeley.edu/~api
api@cs.berkeley.edu