ASAP: Fast, Approximate Graph Pattern Mining at Scale

Anand Iyer et al. @ OSDI 2018

Presenter: Yunang Chen

ASAP Design Overview

A *S*wift *A*pproximate *P*attern-miner

Navigates tradeoff between result accuracy and latency

Runs on general-purpose distributed dataflow platform

Supports for generalized graph pattern mining algorithms

Graph Pattern Mining

Standard approach: Iterative expansion

Lack of scalability

- Generate exponentially large intermediate candidate sets
- Need to store + exchange them in distributed environment

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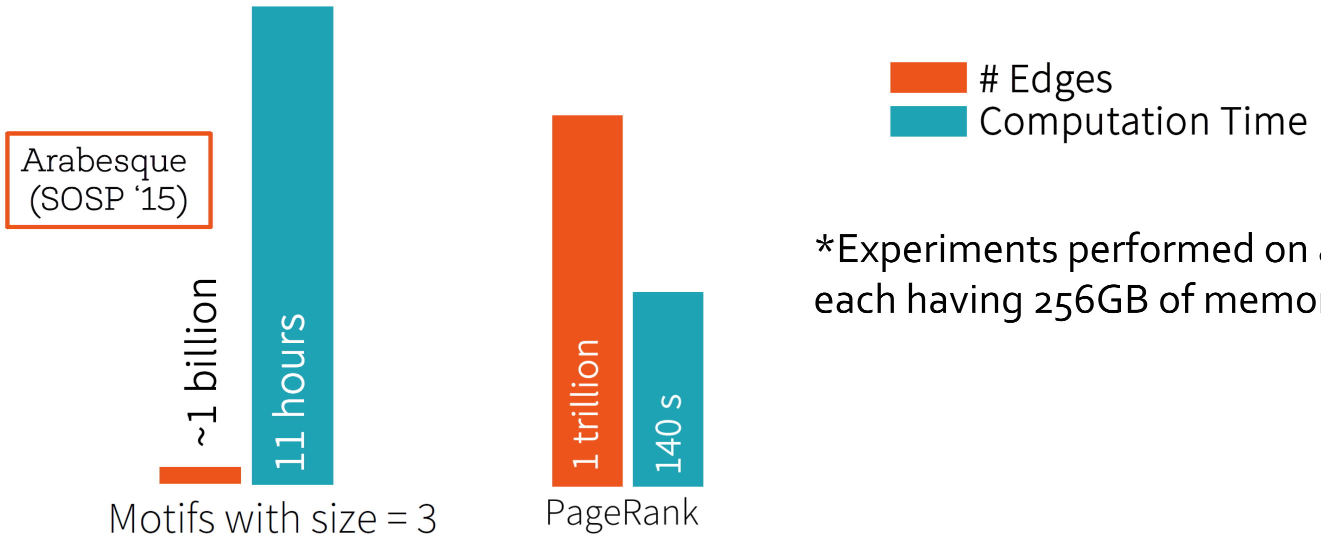


*Experiments performed on a cluster of 20 machines, each having 256GB of memory.

Graph Pattern Mining

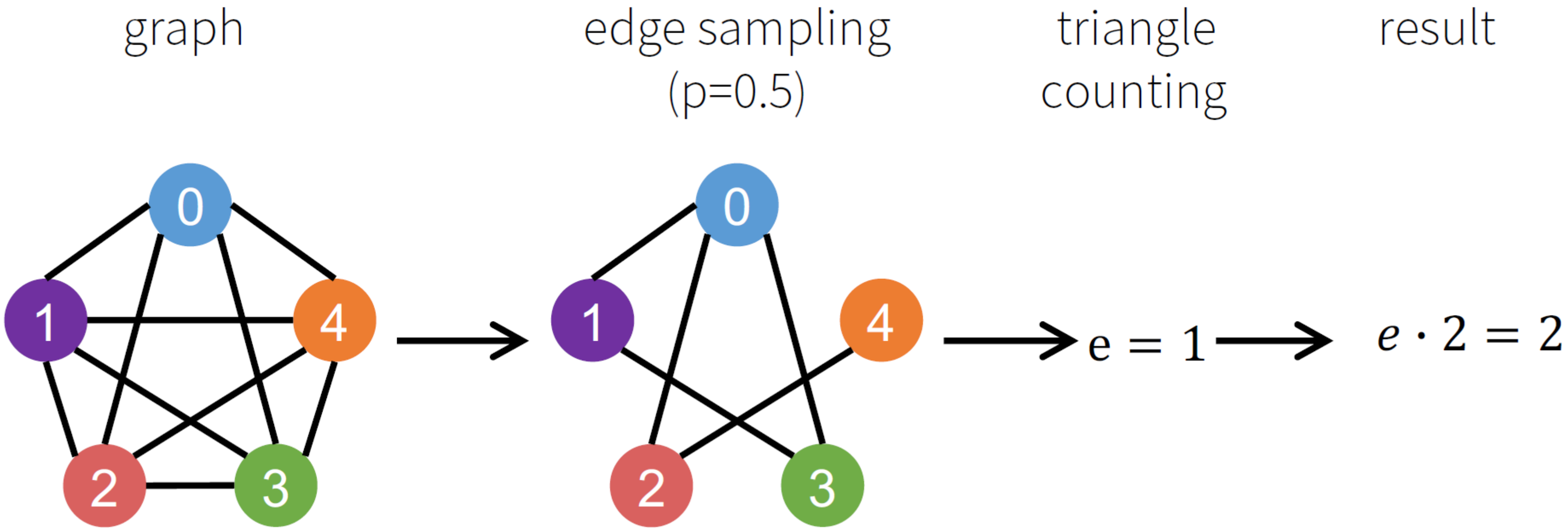
Many pattern mining tasks do not need exact answers.

- Frequent sub-graph mining (FSM) finds the frequency of subgraphs but with an end-goal of ordering them by occurrences.

Leverage approximation for pattern mining

Approximate Pattern Mining

Previous approach: Apply the exact same algorithm on subsets of the input data, then use the statistical properties of these subsets to estimate final results.



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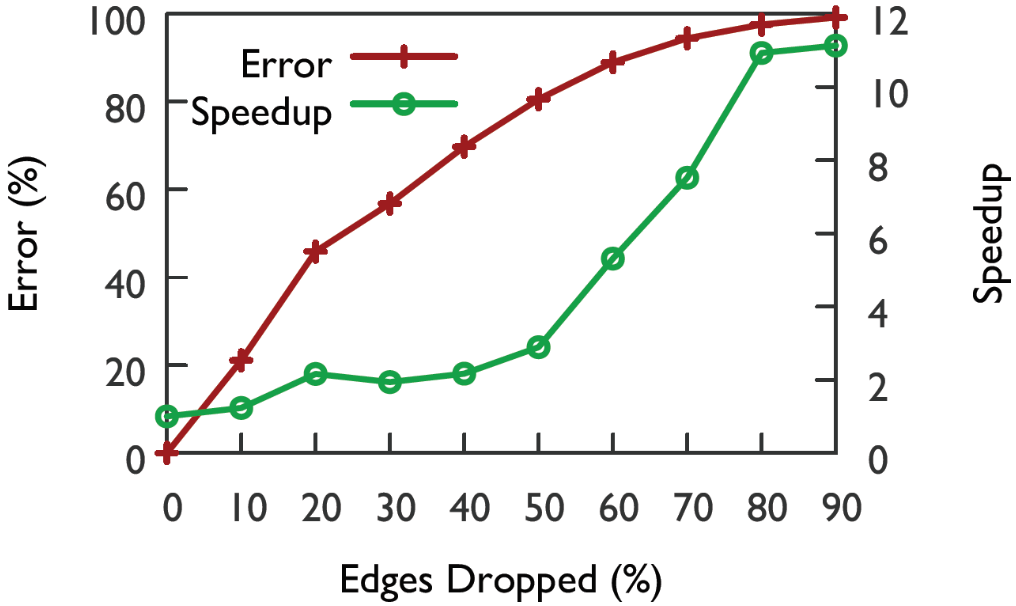
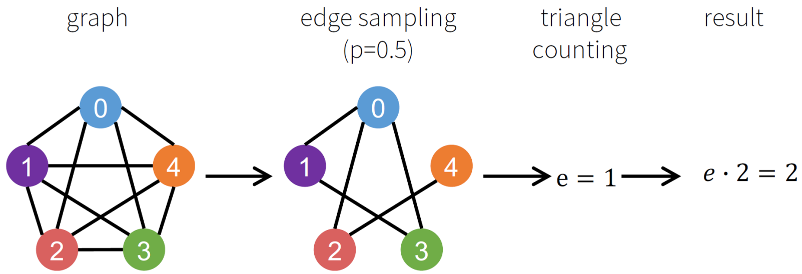




- No significant speedup
- Large error rate

Approximate Pattern Mining

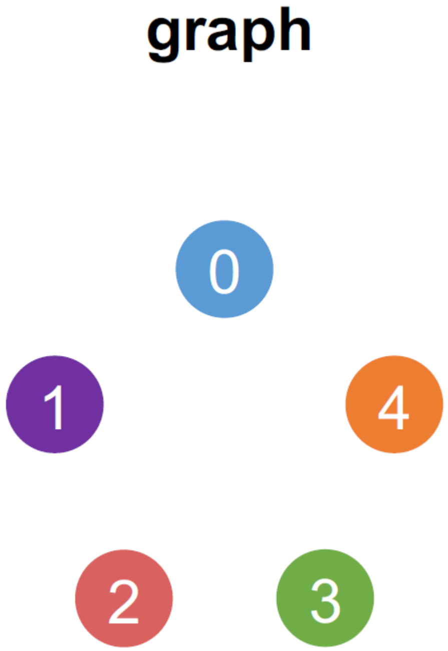
Neighborhood sampling:

1. Model the edges in the graph as a stream
2. Sample one edge, e_1
3. Gradually add more adjacent edges, $e_2, \ldots, e_k$
4. Stop when the edges form the pattern or becomes impossible to do so
5. Use the probability of sampling to bound the total number of occurrences of the pattern:
   $P(e_1, \ldots, e_k) = P(e_1) \times P(e_2 \mid e_1) \times \ldots \times P(e_k \mid e_1, \ldots, e_{k-1})$
6. Repeat Step 1-5 multiple times

Approximate Pattern Mining

Neighborhood sampling: Triangle Counting

1. Model the edges in the graph as a stream

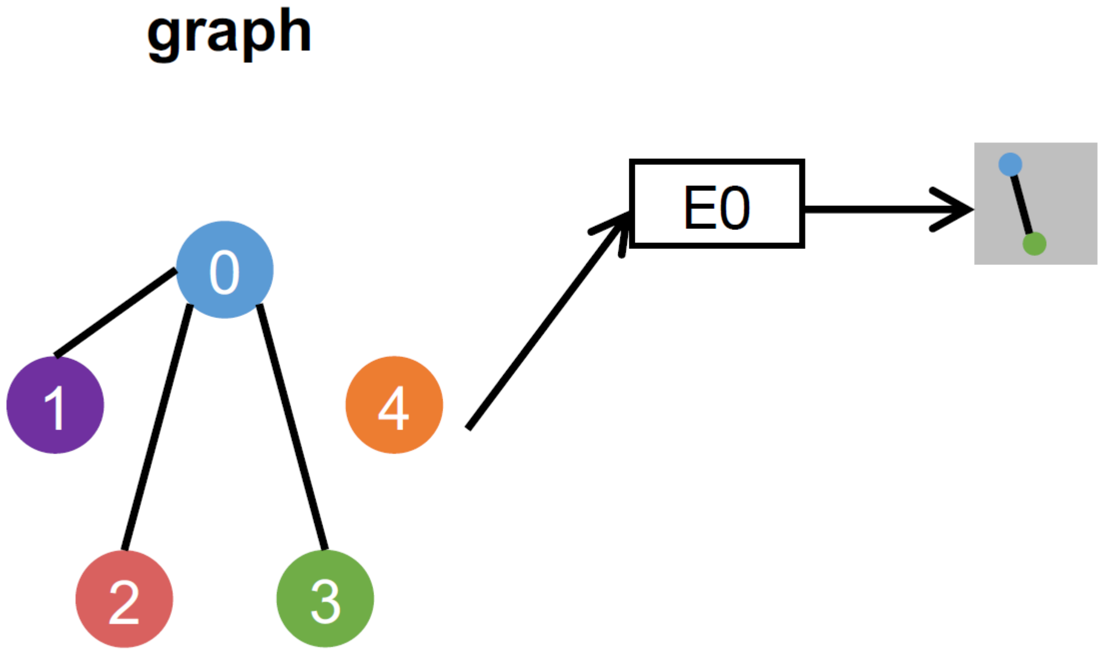


edge stream: (0,1), (0,2), (0,3), (0,4), (1,2), (1,3), (1,4), (2,3), (2,4), (3,4)

Approximate Pattern Mining

Neighborhood sampling: Triangle Counting

2. Sample one edge



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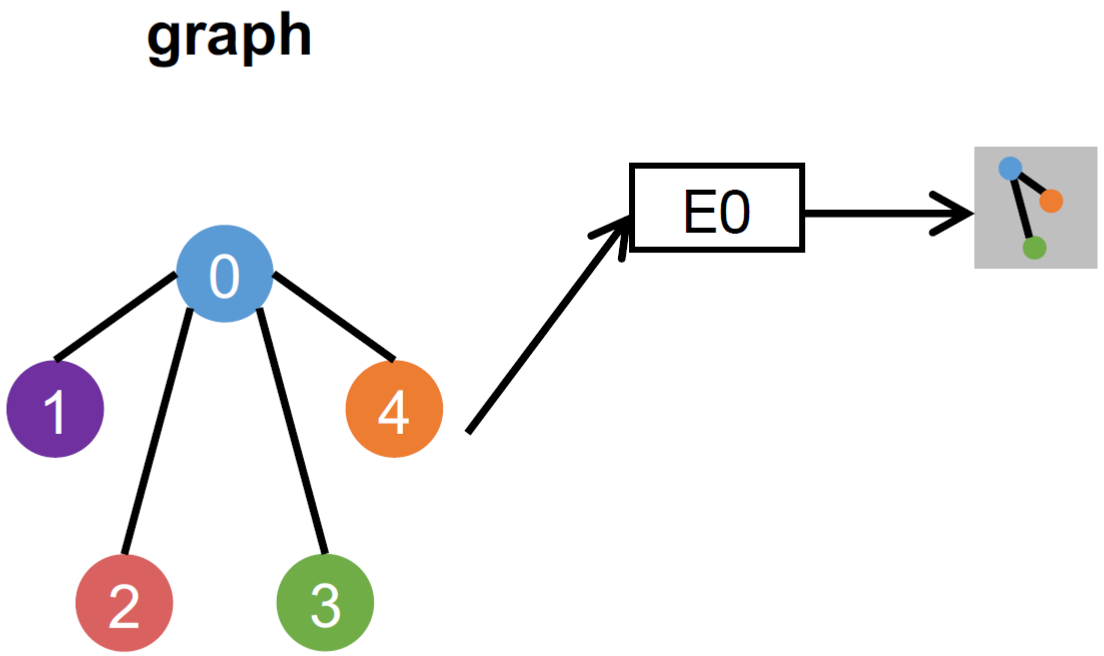
Approximate Pattern Mining

Neighborhood sampling: Triangle Counting

3. Gradually add more adjacent edges



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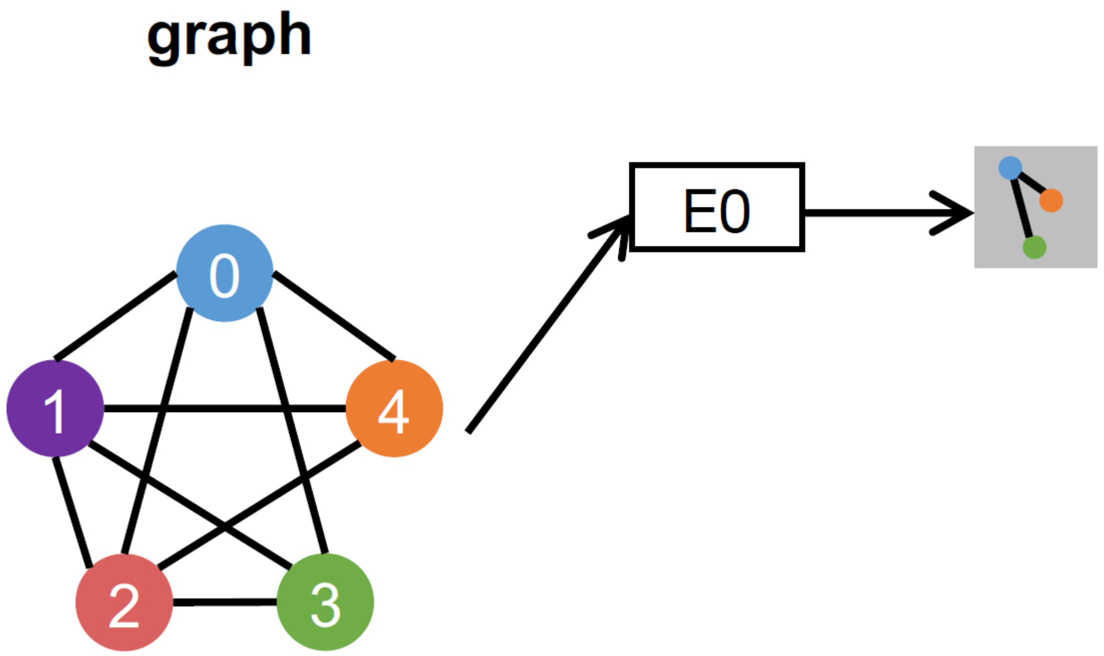
Approximate Pattern Mining

Neighborhood sampling: Triangle Counting

4. Stop when the edges form the pattern or becomes impossible to do so



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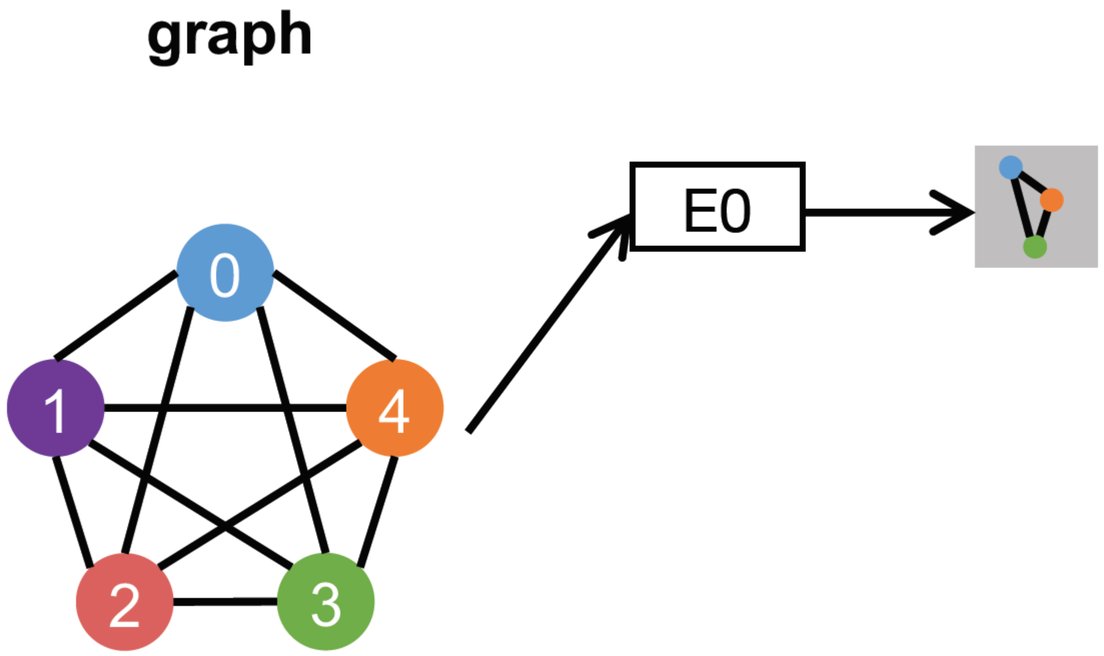

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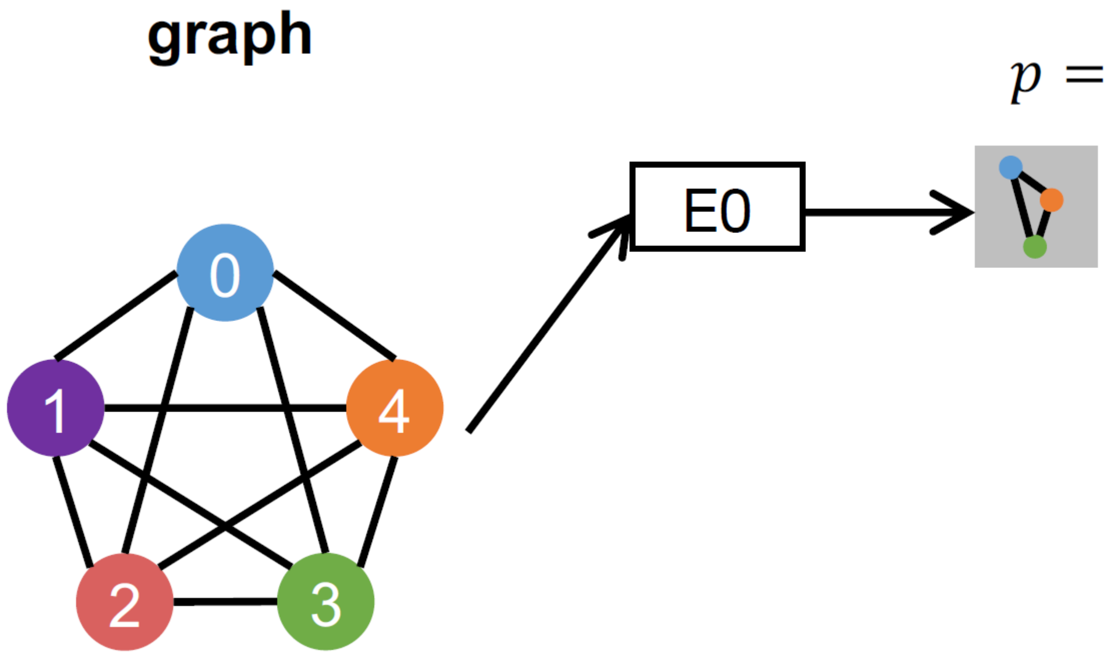
Approximate Pattern Mining

Neighborhood sampling: Triangle Counting

5. Use the probability of sampling to bound the total number of occurrences



$$p = \frac{1}{10} * \frac{1}{4}$$

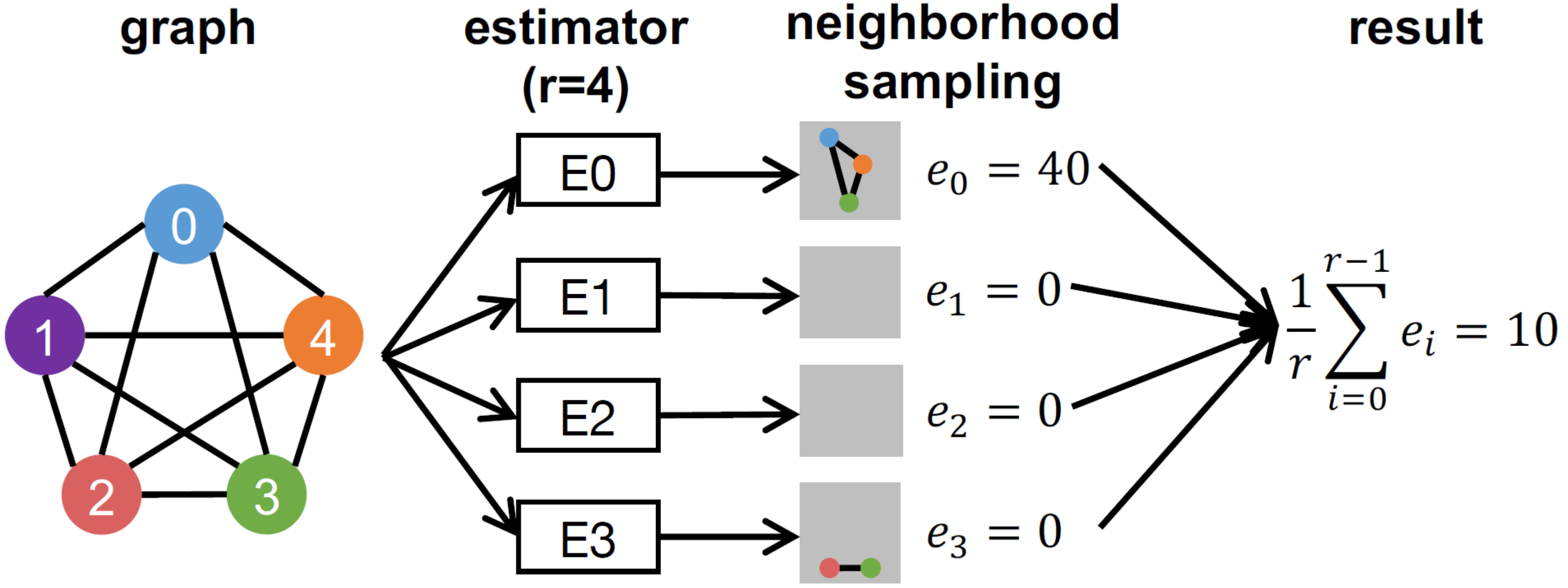
$$e_0 = 40$$

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

Approximate Pattern Mining

Neighborhood sampling: Triangle Counting

6. Repeat Step 1-5 multiple times



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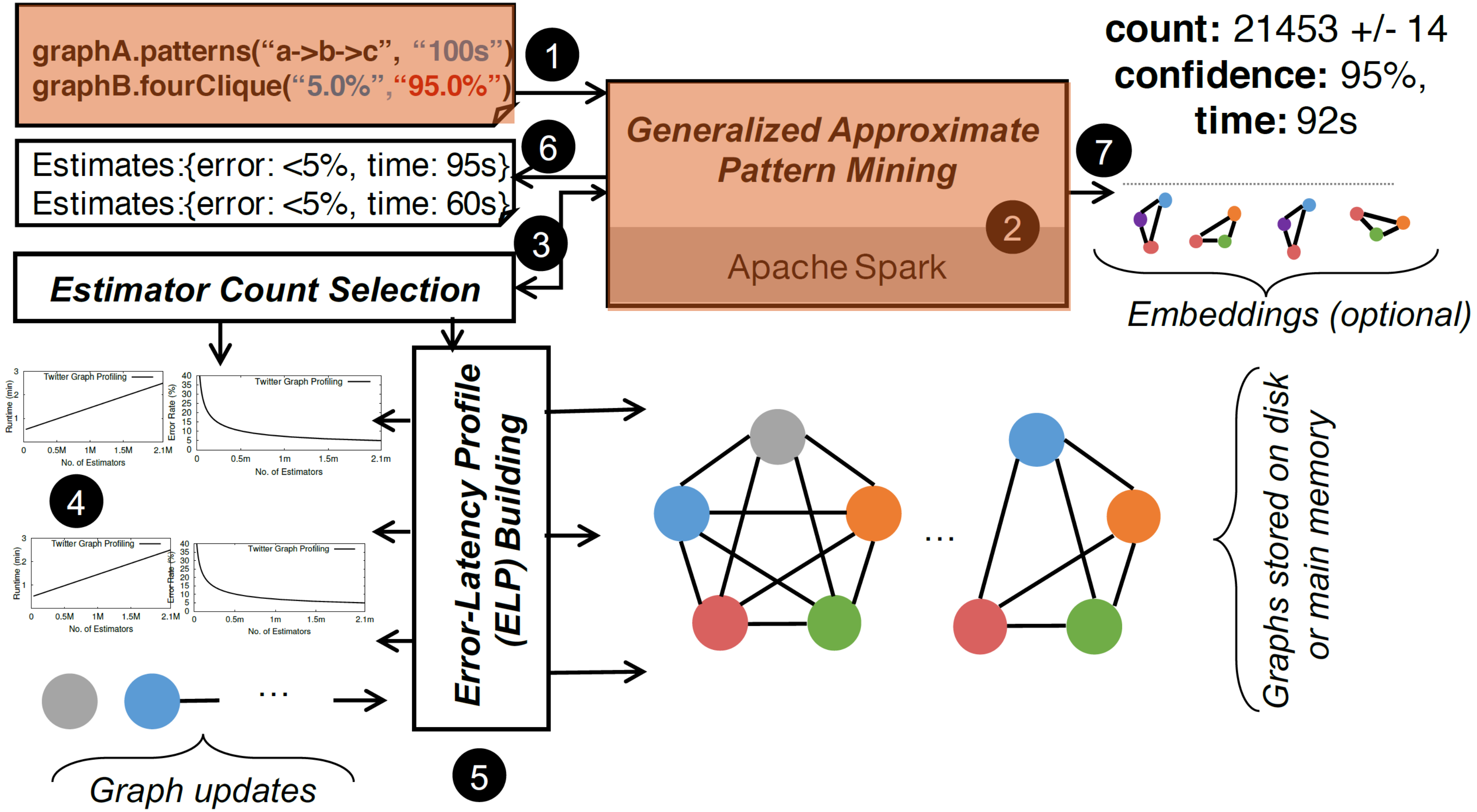
ASAP Architecture



Programming API

Neighborhood sampling:

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API
`sampleVertex`: $() \rightarrow (v, p)$
`SampleEdge`: $() \rightarrow (e, p)$
`ConditionalSampleVertex`: `(subgraph)` $\rightarrow (v, p)$
`ConditionalSampleEdge`: `(subgraph)` $\rightarrow (e, p)$
`ConditionalClose`: `(subgraph, subgraph)` $\rightarrow boolean$

Programming API

```
(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)
else return 0
```

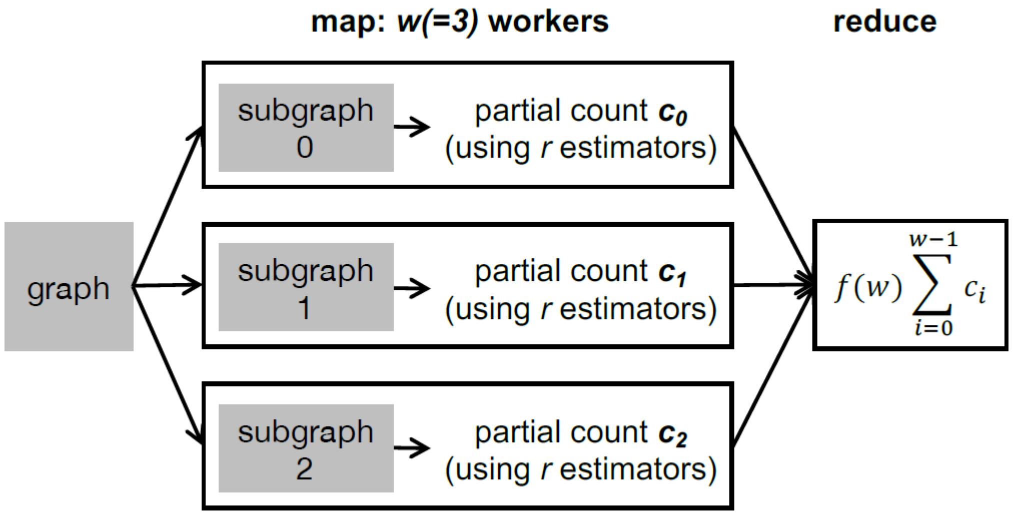
Sampling Phase: fix the vertices for a pattern

Closing Phase: waiting for remaining edges to complete the pattern

Distributed Execution

Rely on map and reduce operations

1. Partition the vertices across w workers
2. Apply estimator task on each subgraph to produce a partial count
3. Sum up partial counts
4. Adjust for underestimation by multiplying $f(w)$
   e.g. for triangle count, $f(w)=1/w^2$



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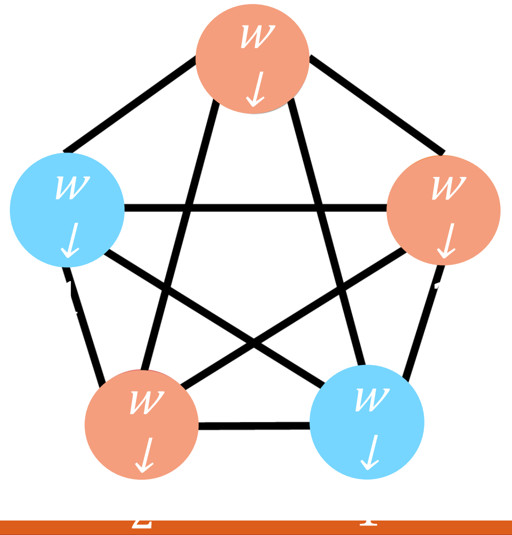
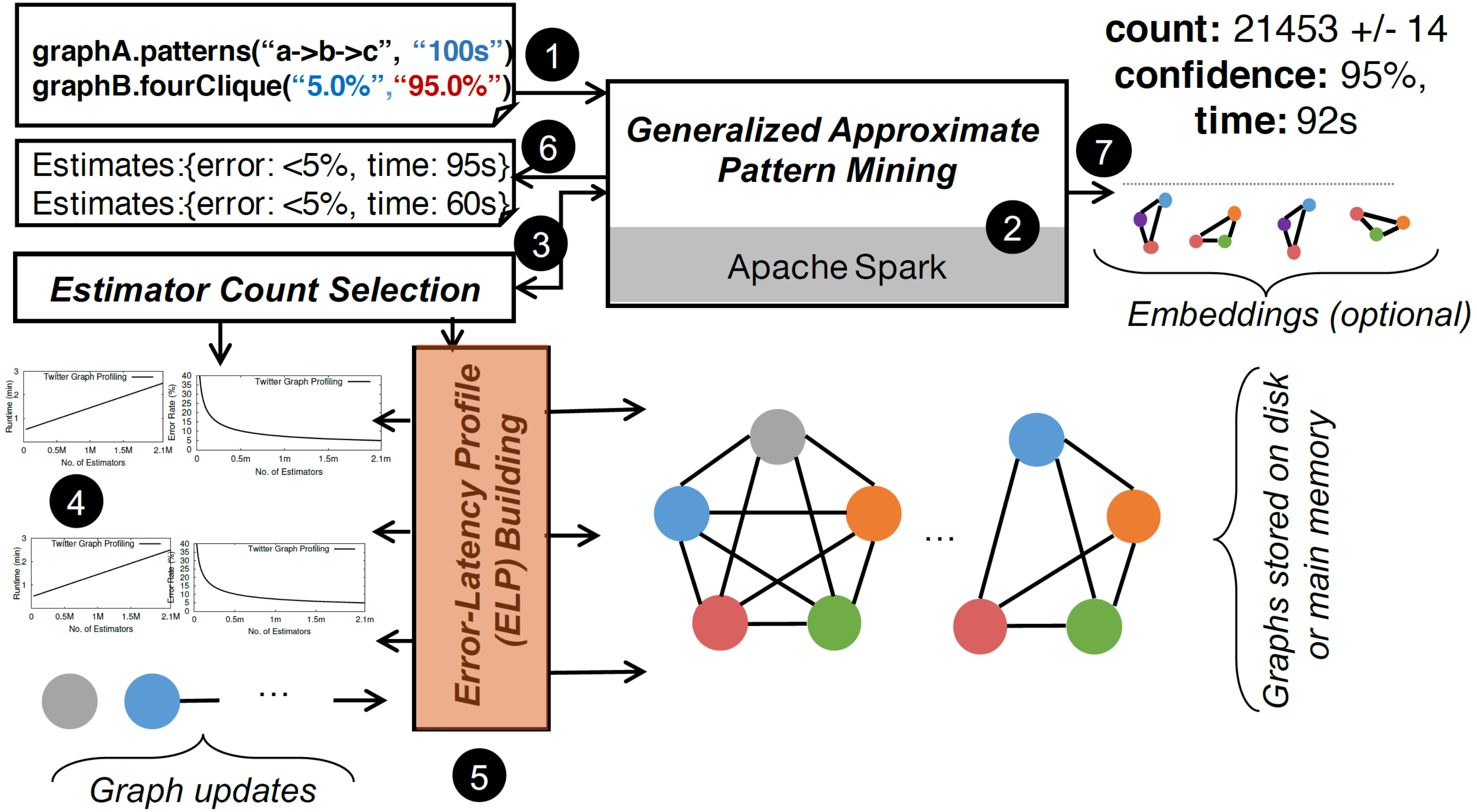
   e.g. for triangle count, $f(w) = w \uparrow 2$

- Patterns across partitions are ignored
- Total occurrence is reduced by $1/f(w)$



ASAP Architecture

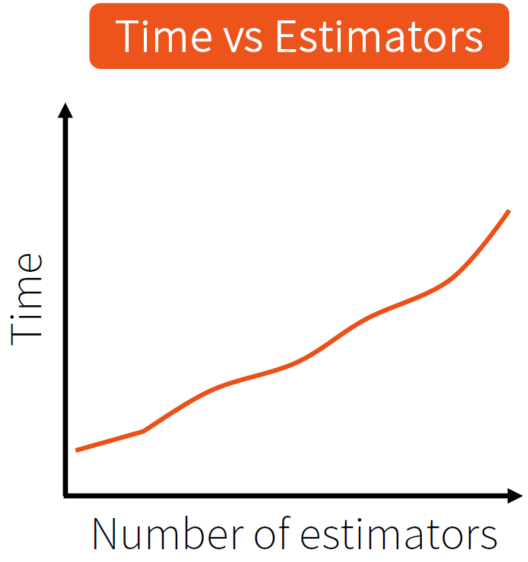


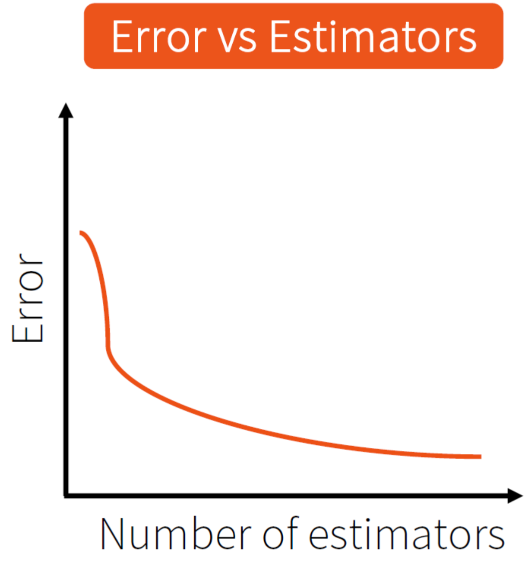
Error-Latency Profile (ELP)

ASAP can perform tasks in two modes:

- Time budget T
- Error budget ϵ

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

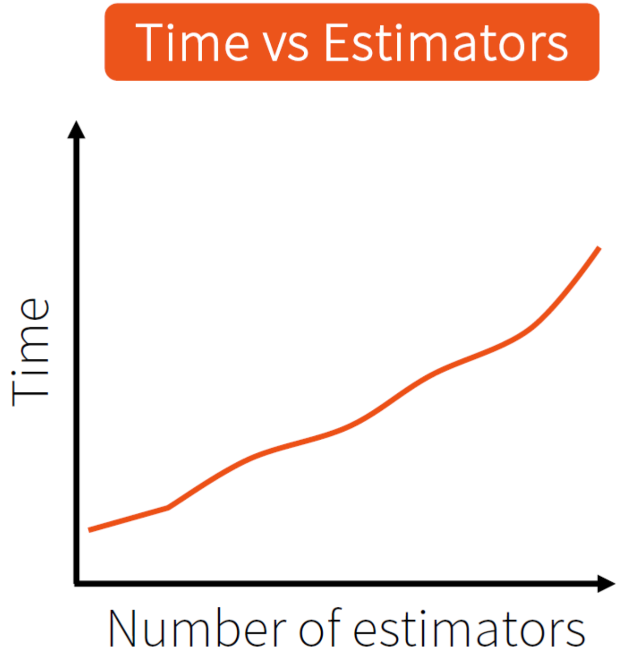




Error-Latency Profile (ELP)

Running time scales linearly with number of estimators

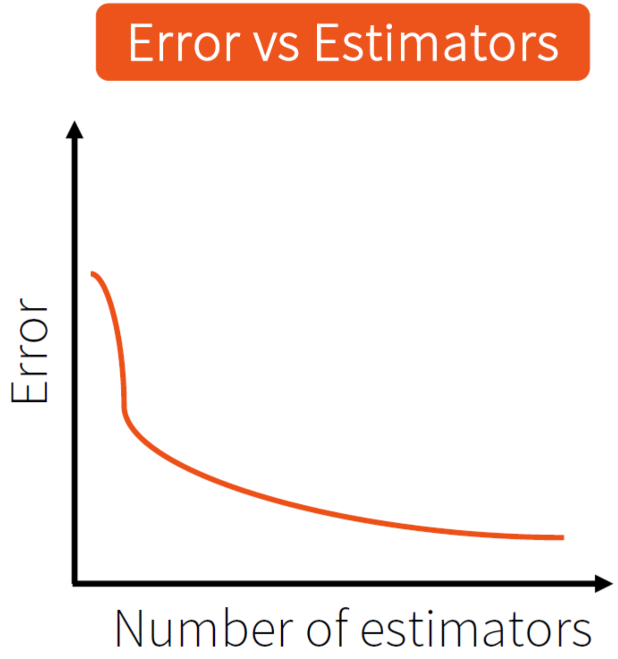
Test exponentially spaced points + extrapolation to build a linear model



Error-Latency Profile (ELP)

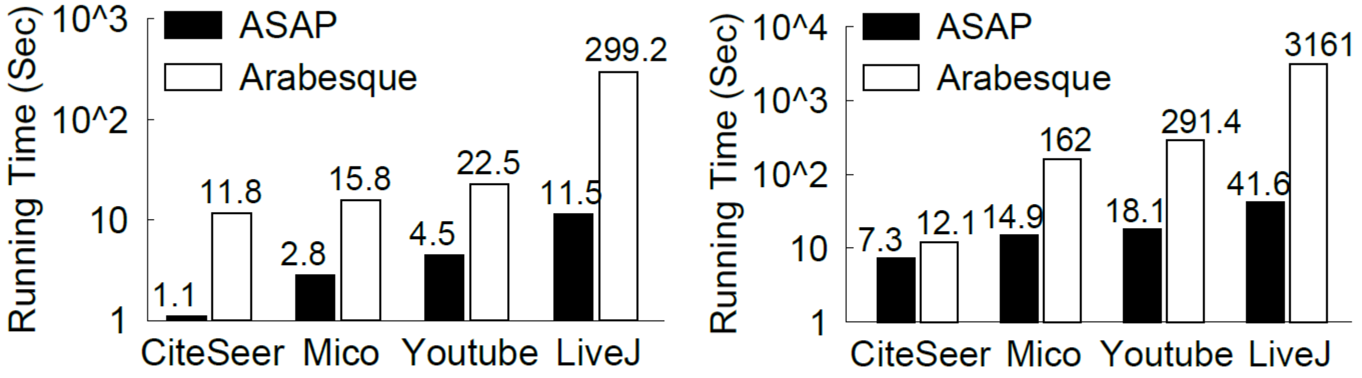
Chernoff bound for triangle counting: $N_e > K \times m \times \Delta / \epsilon^2 P$

Estimate ground truth P_s on a small sample of the graph + scale to P



Evaluation

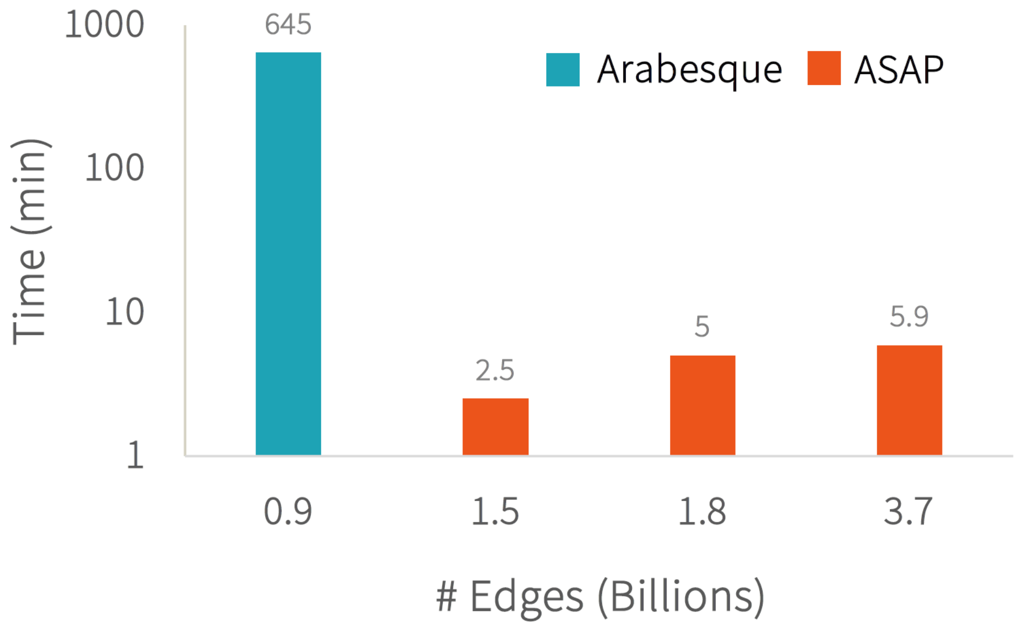
77x speedup with under 5% loss of accuracy for smaller graphs (0.01-30 million edges)



(a) 3-Motif Counting **(b)** 4-Motif Counting

Evaluation

258x speedup with under 5% loss of accuracy for larger graphs



Conclusion

ASAP is the first system that does fast, scalable approximate graph pattern mining on large graphs.

ASAP outperforms Arabesque by more than a magnitude faster with a sacrifice of 5% accuracy.

ASAP scales to larger graphs whereas Arabesque fails to complete execution.

Reference

- https://www.usenix.org/sites/default/files/conference/protected-files/osdi18_slides_iyer.pdf
- Iyer, Anand Padmanabha, et al. "ASAP: fast, approximate graph pattern mining at scale." *Proceedings of the 12th USENIX conference on Operating Systems Design and Implementation*. USENIX Association, 2018.
- Iyer, Anand Padmanabha, et al. "Towards fast and scalable graph pattern mining." 10th {USENIX} Workshop on Hot Topics in Cloud Computing (HotCloud 18). USENIX} Association}, 2018.