Towards Fast and Scalable Graph Pattern Mining

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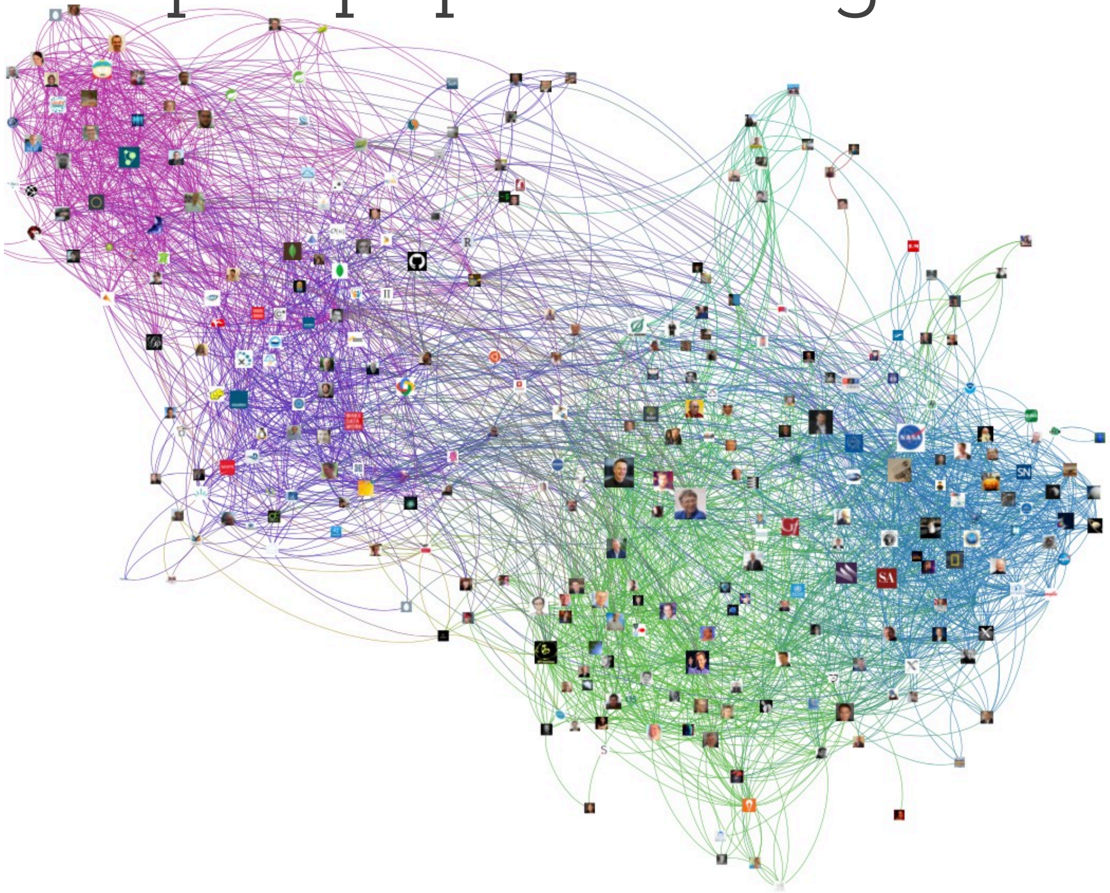
[★] UC Berkeley [◆] Johns Hopkins University [▲] Microsoft Research / University of Wisconsin

HotCloud, July 09, 2018

riselab UC Berkeley

Graphs popular in big data analytics



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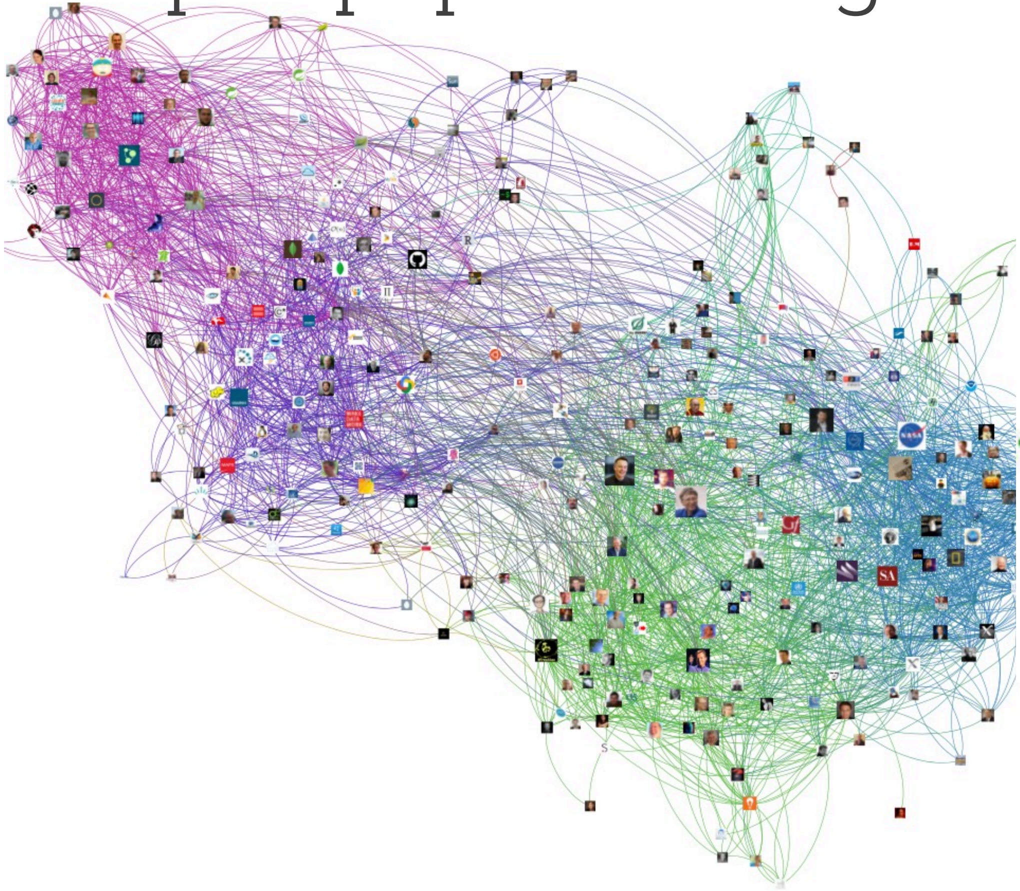

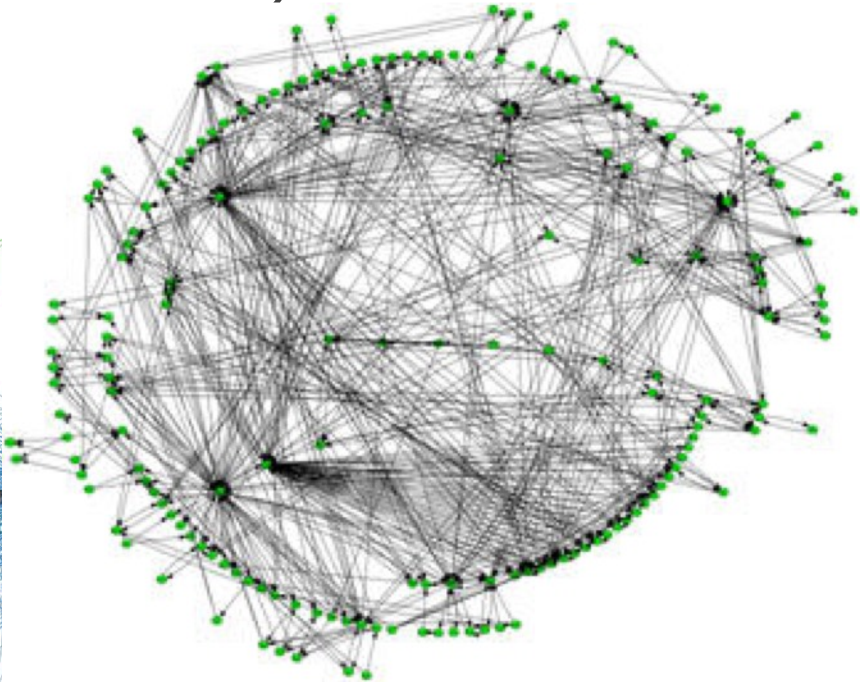

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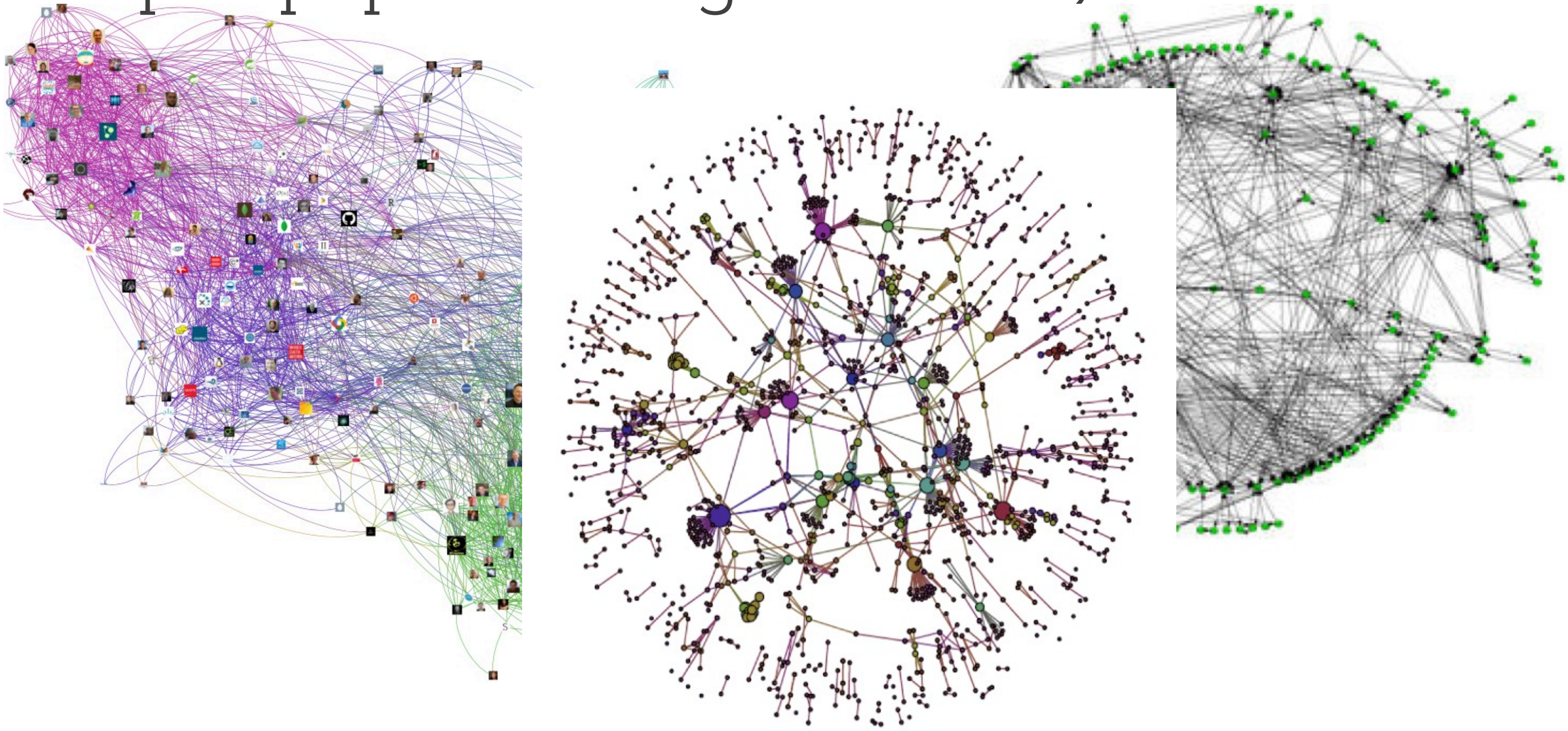
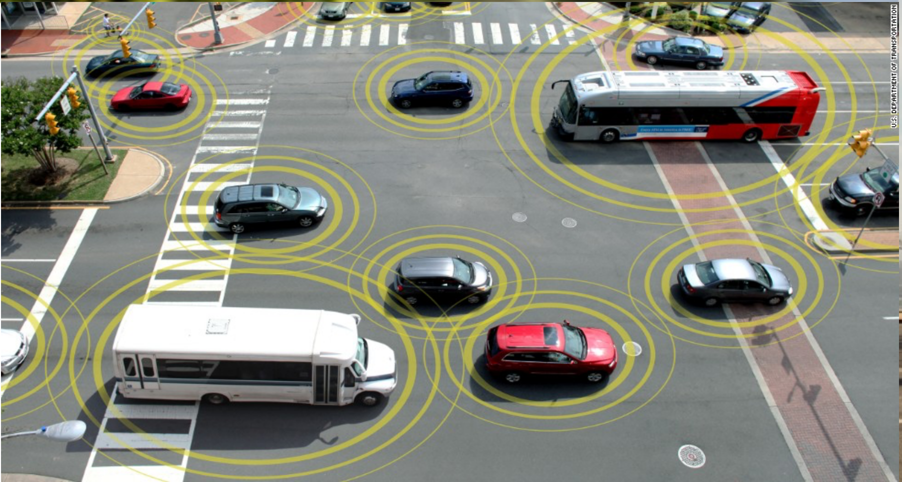



U.S. DEPARTMENT OF TRANSPORTATION


Google
self-driving car

Graph Analytics

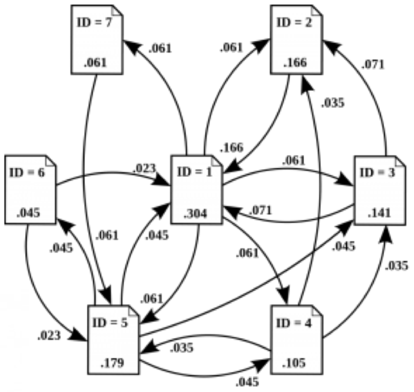
Graph Analytics

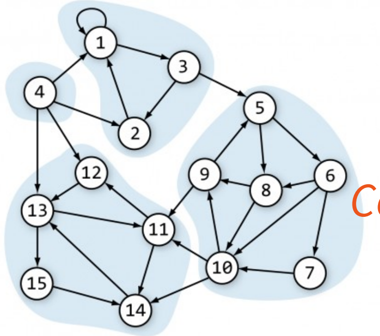
Processing Algorithms

Graph Analytics

Processing Algorithms

PageRank





Connected Components

Graph Analytics

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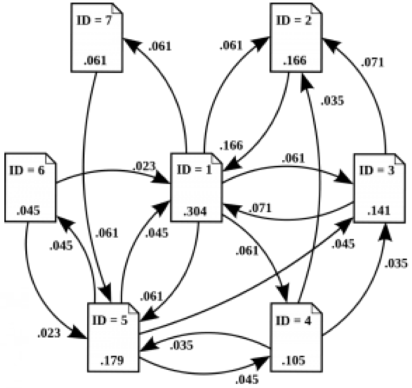

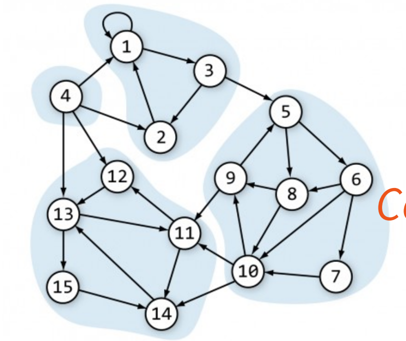

Connected Components

Mining Algorithms

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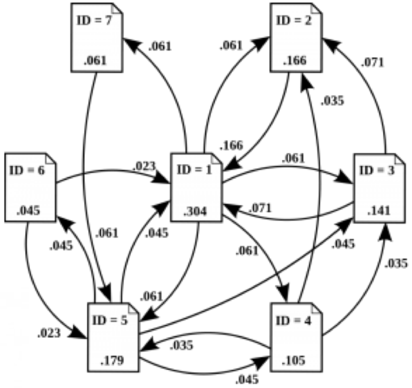

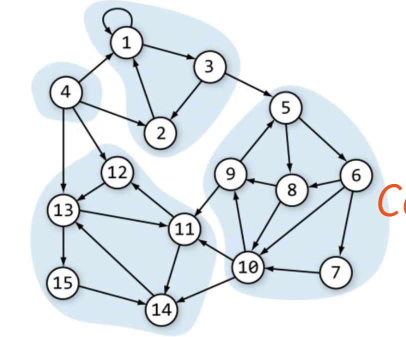

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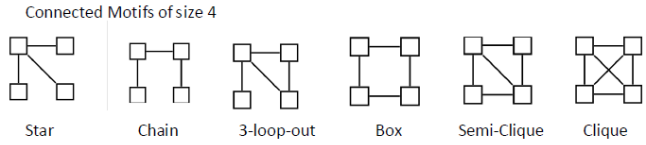
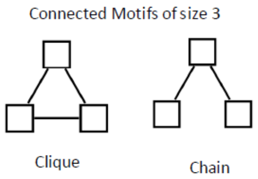
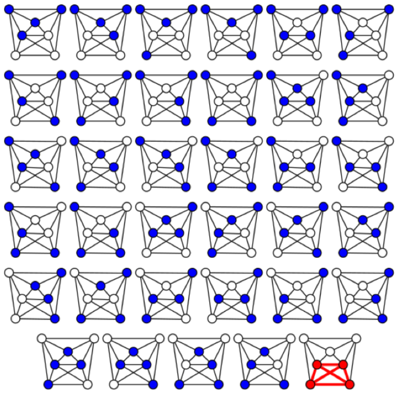




Motifs

Cliques



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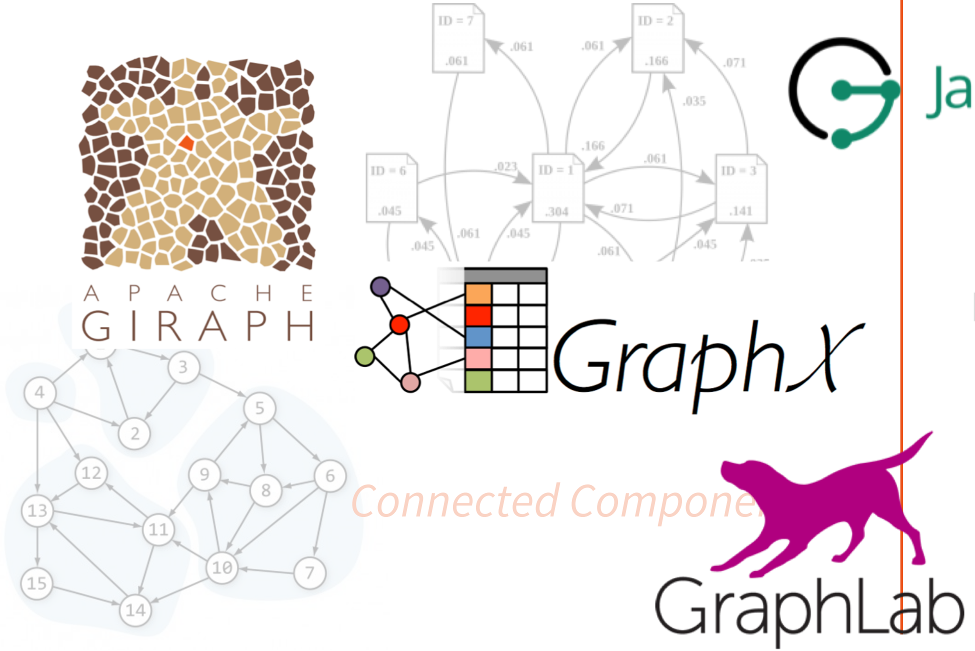

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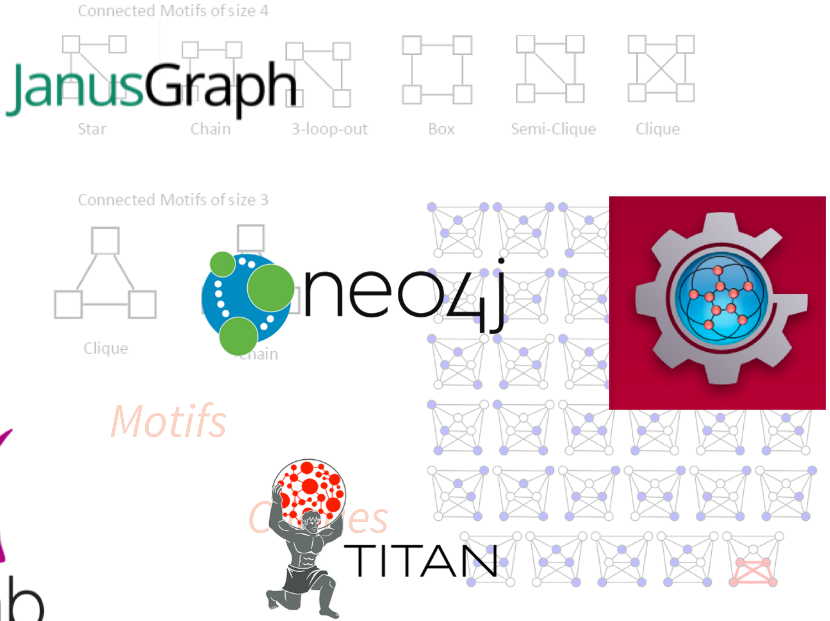

Graph Analytics: State-of-the-Art

Processing Algorithms

Computes properties of the underlying graph

Mining Algorithms

Discovers structural patterns in the underlying graph

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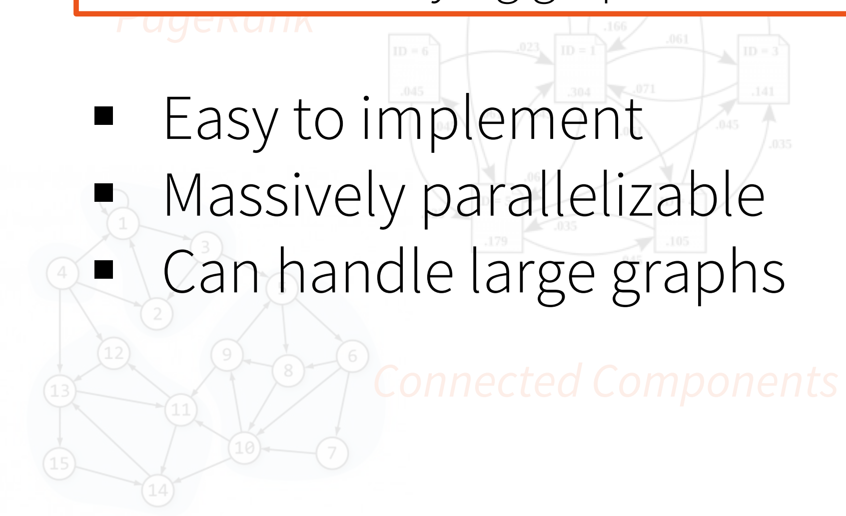
- Can handle large graphs



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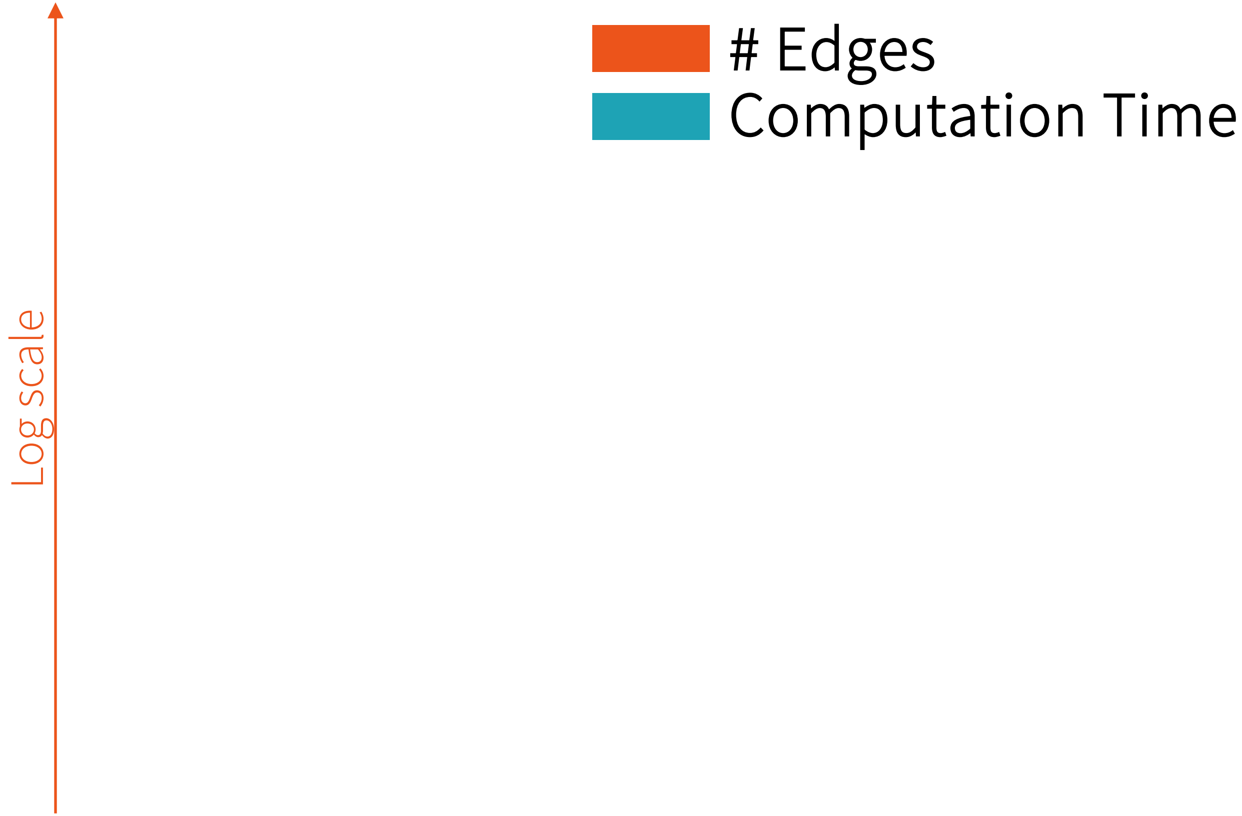
Challenging to mine patterns in large graphs

Graph Analytics: Processing vs Mining



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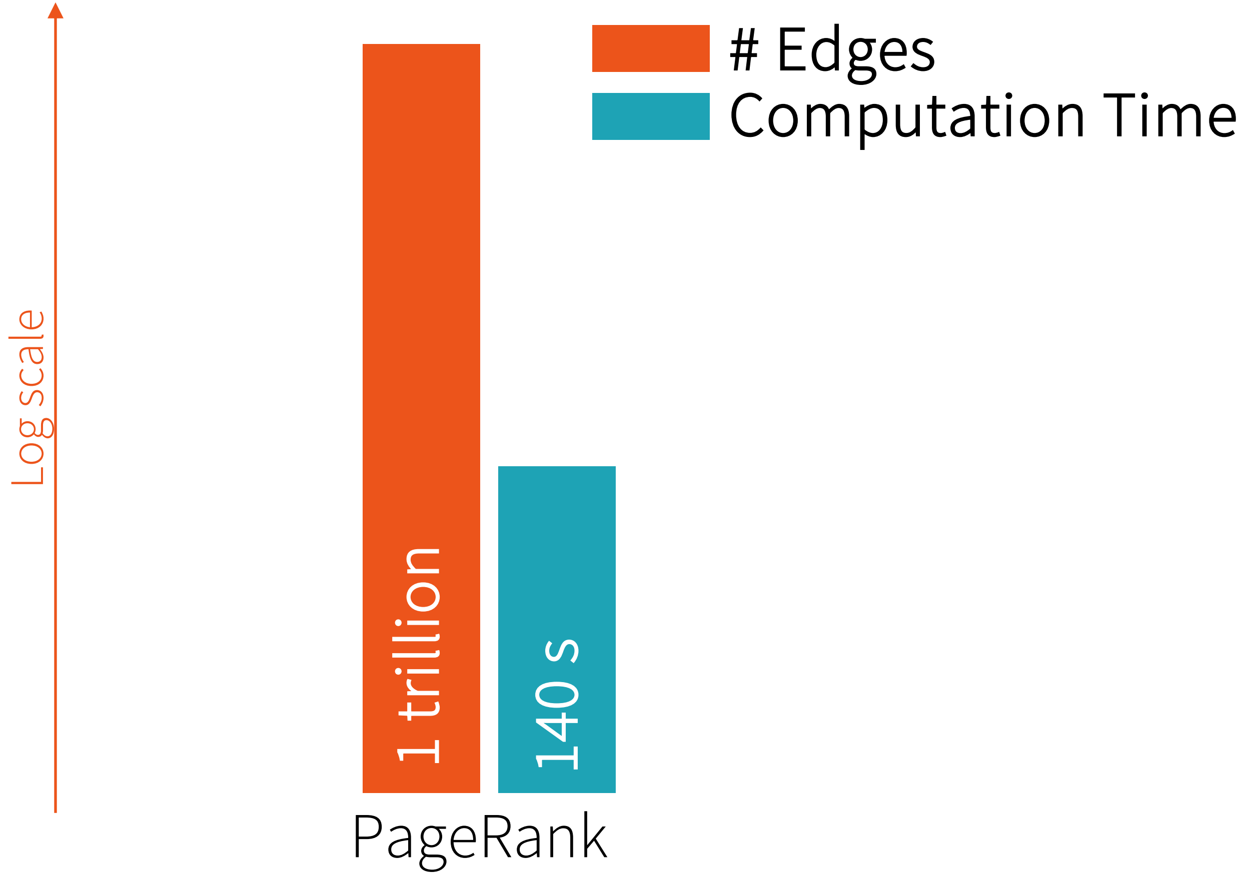

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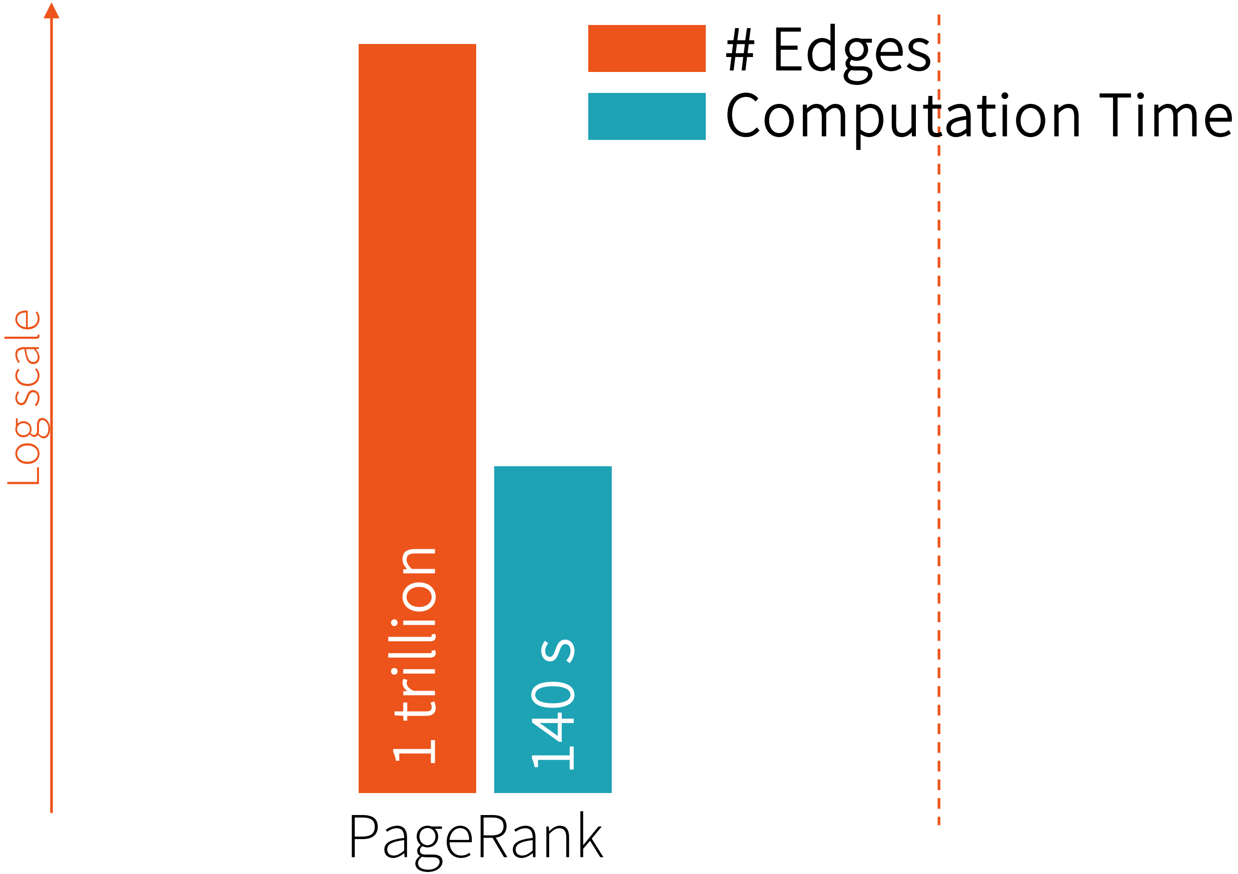

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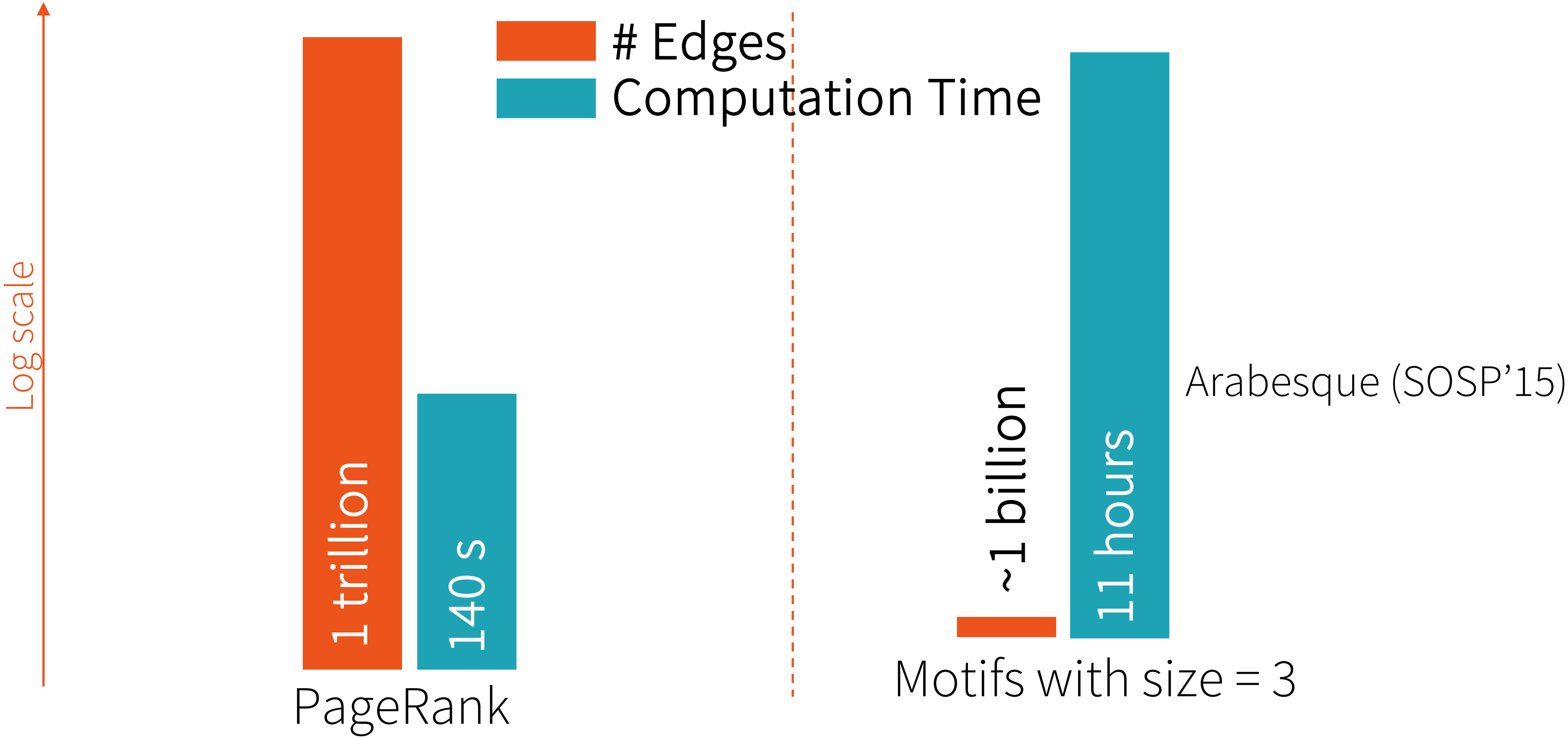

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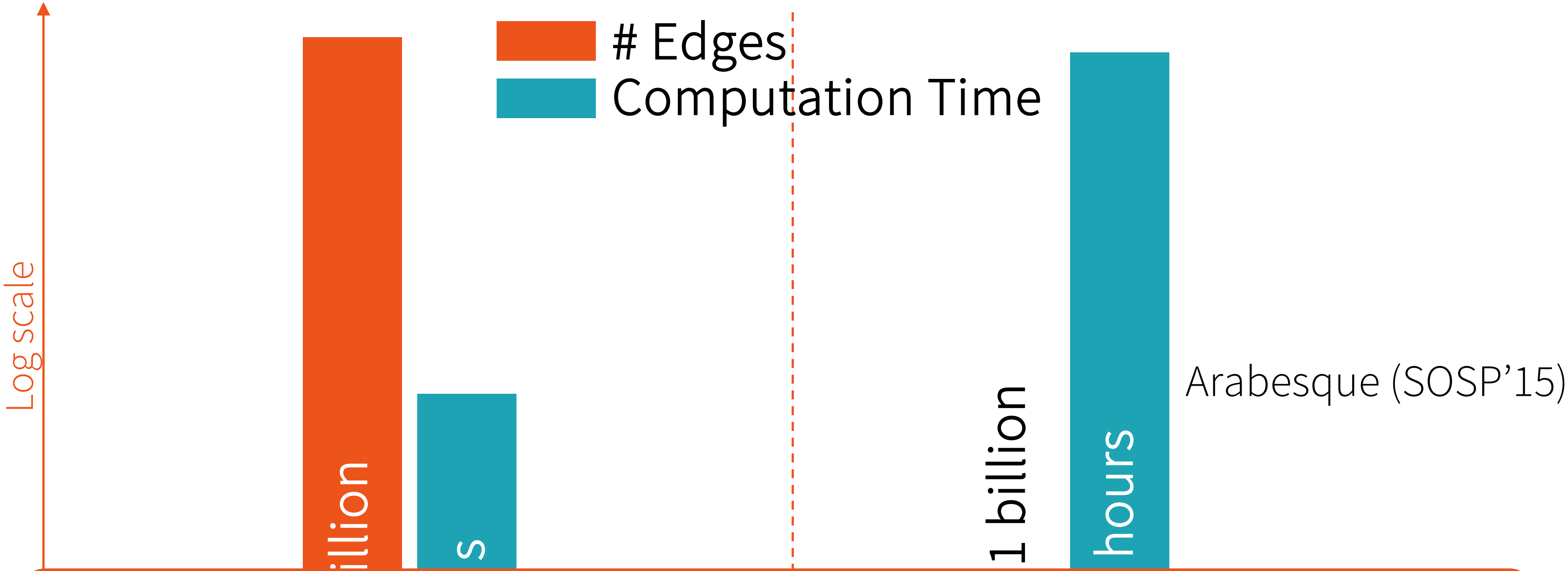

Can graph pattern mining be made both *fast* and *scalable*?

Many mining tasks ask for the number of occurrences and do not need *exact* answers

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Leverage *approximation* for graph pattern mining

Approximate Analytics

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

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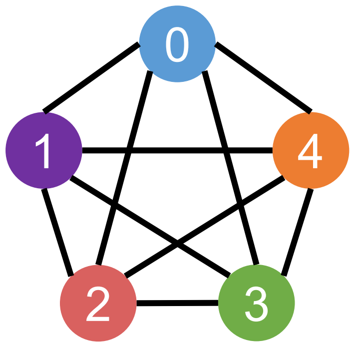
graph



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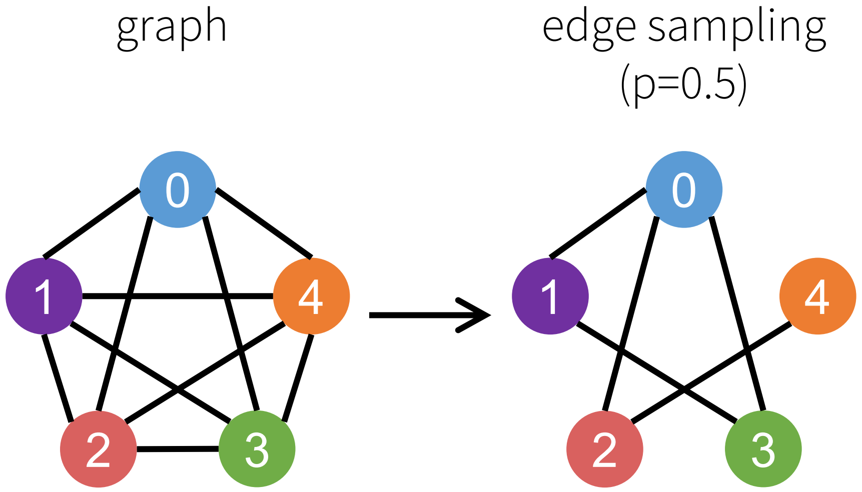

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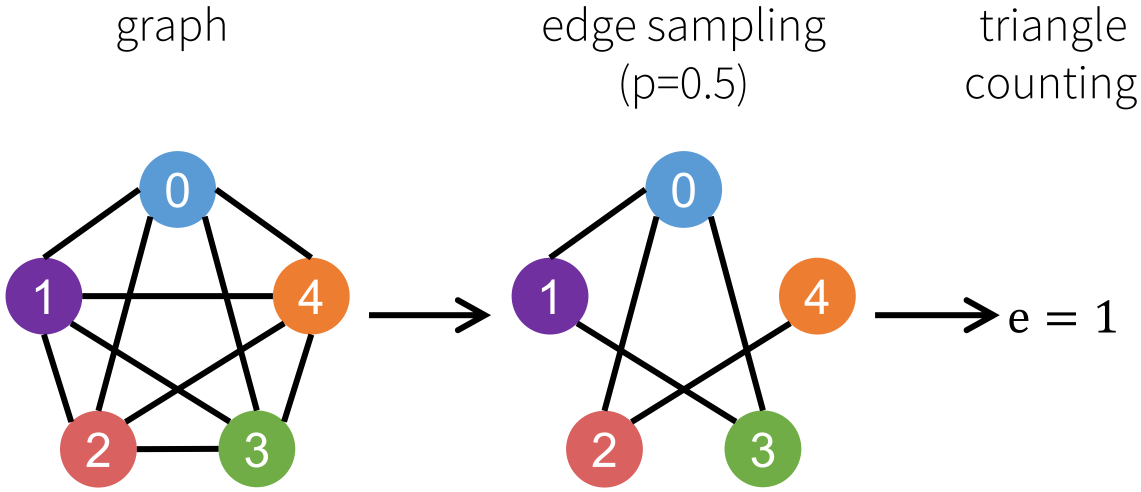

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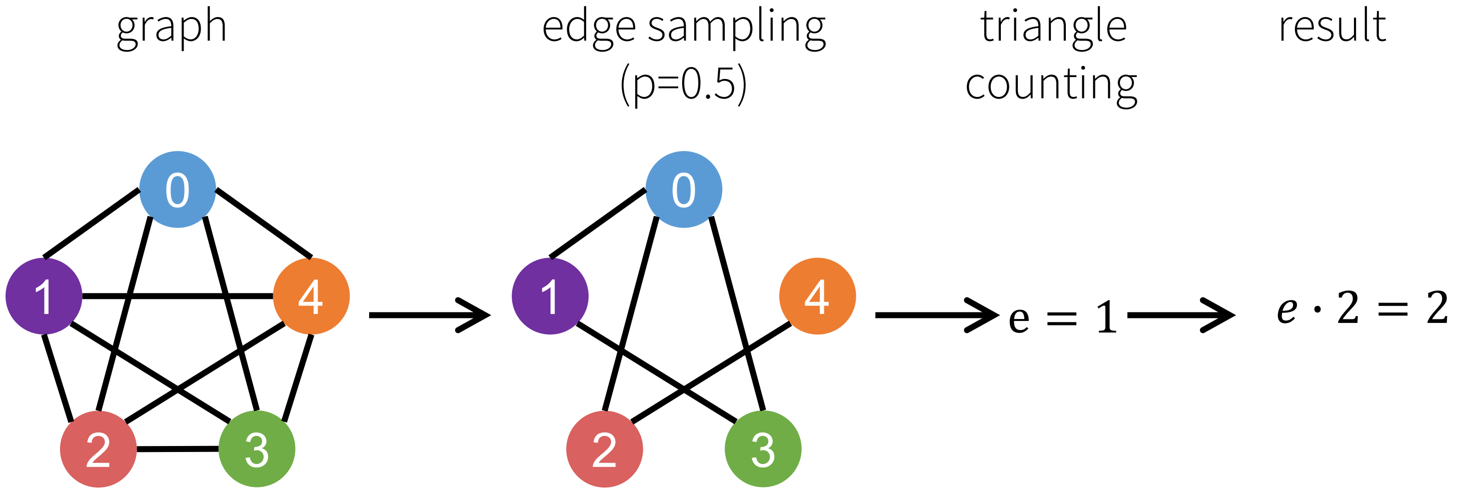

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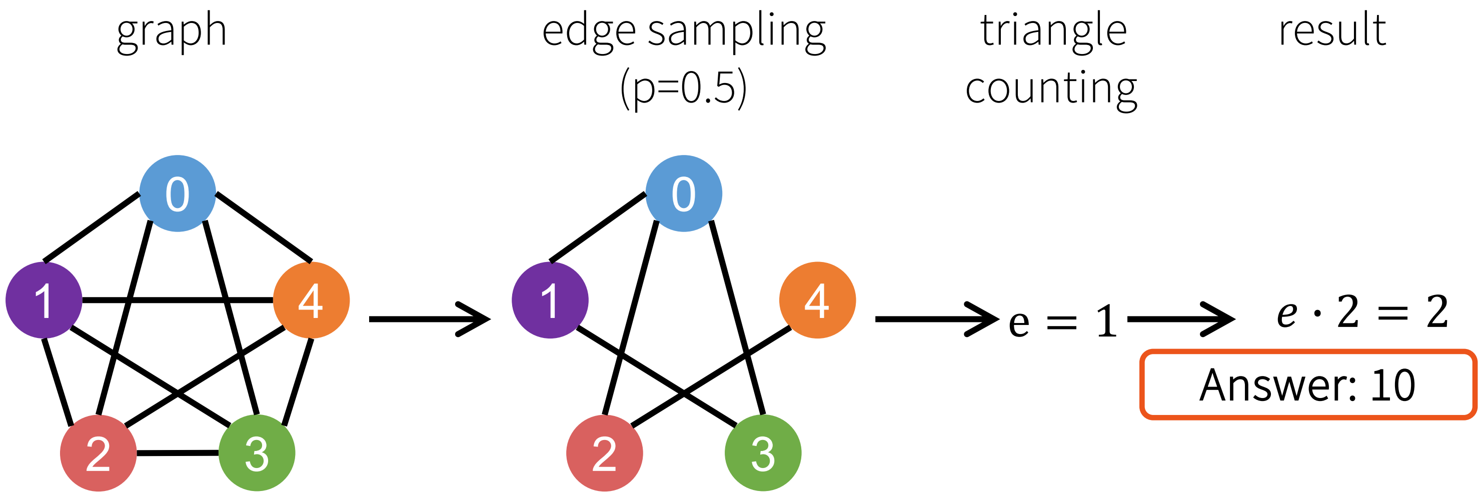

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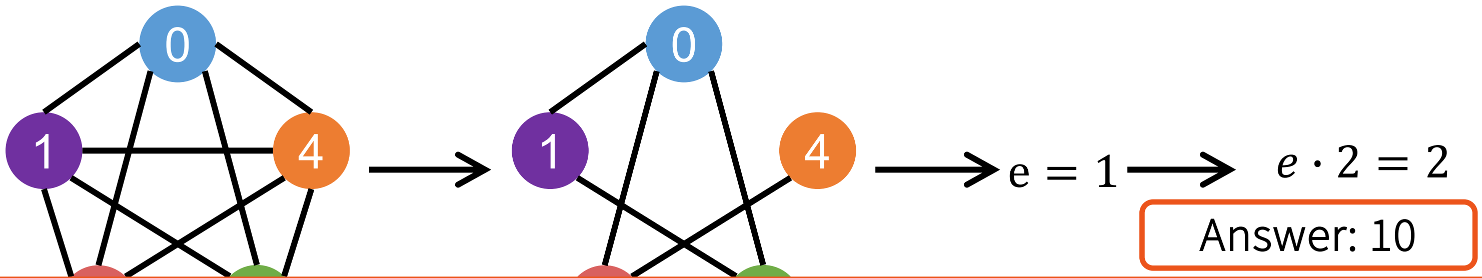
General approach: Apply algorithm on subset(s) (sample) of the input data

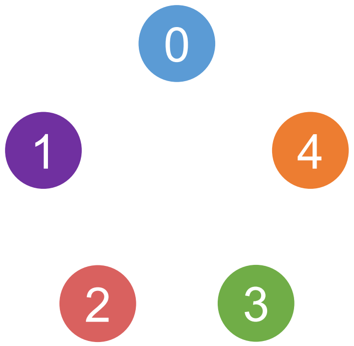
graph | edge sampling (p=0.5) | triangle counting | result



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

Approximation by Sampling Patterns

graph



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

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

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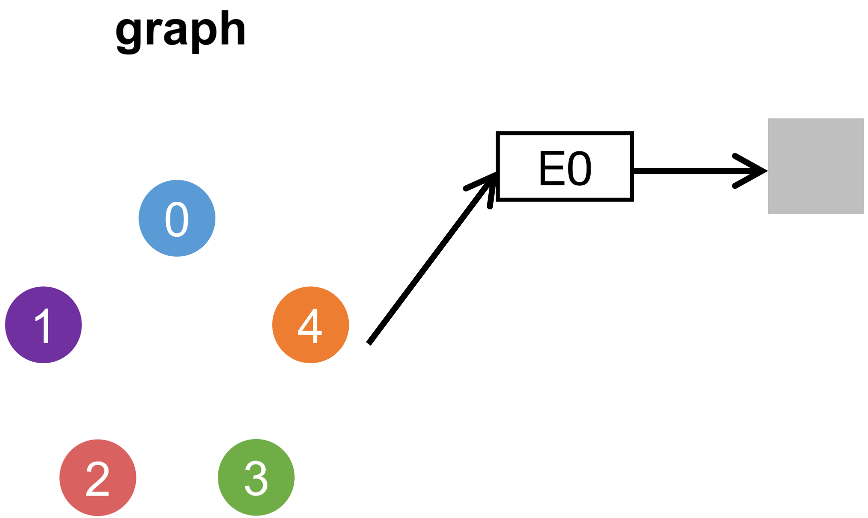

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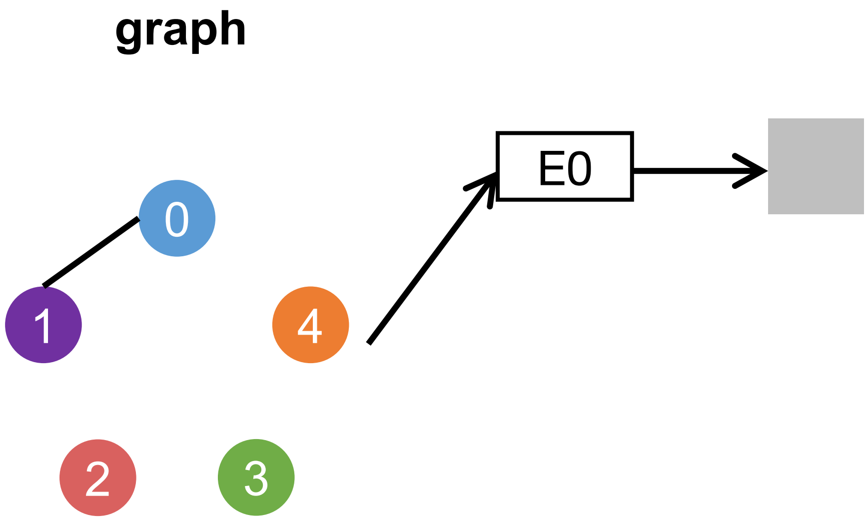

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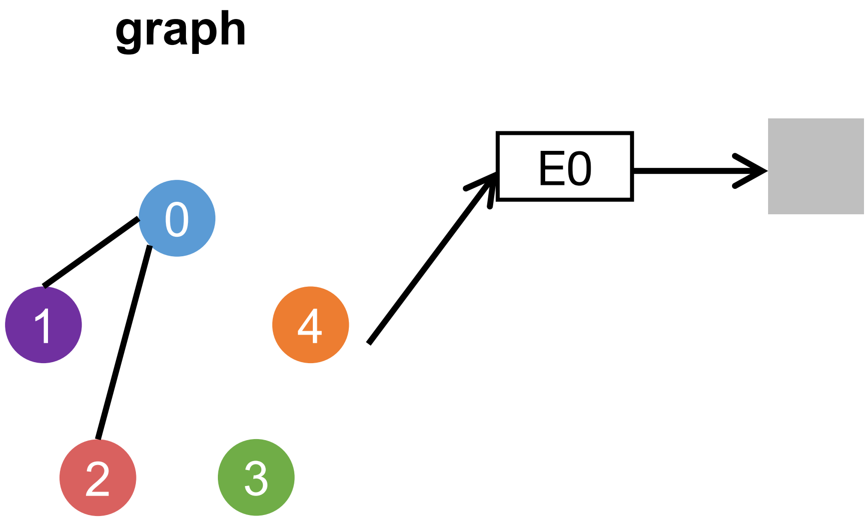

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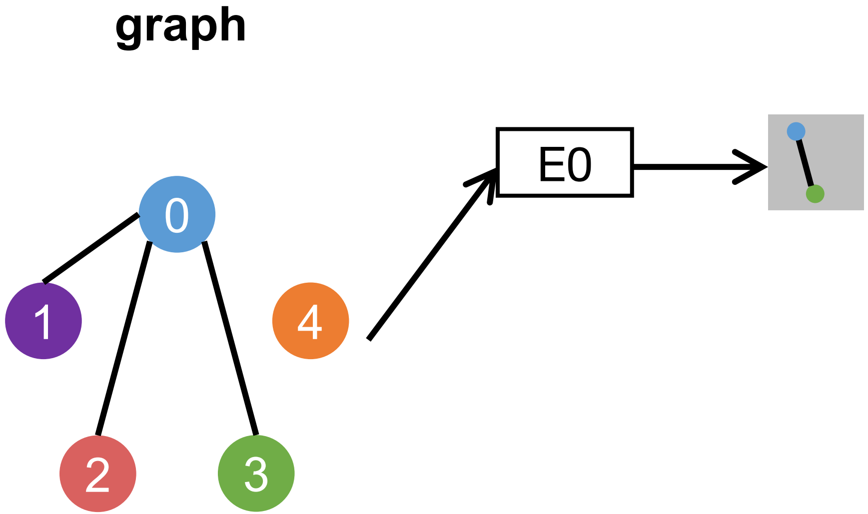

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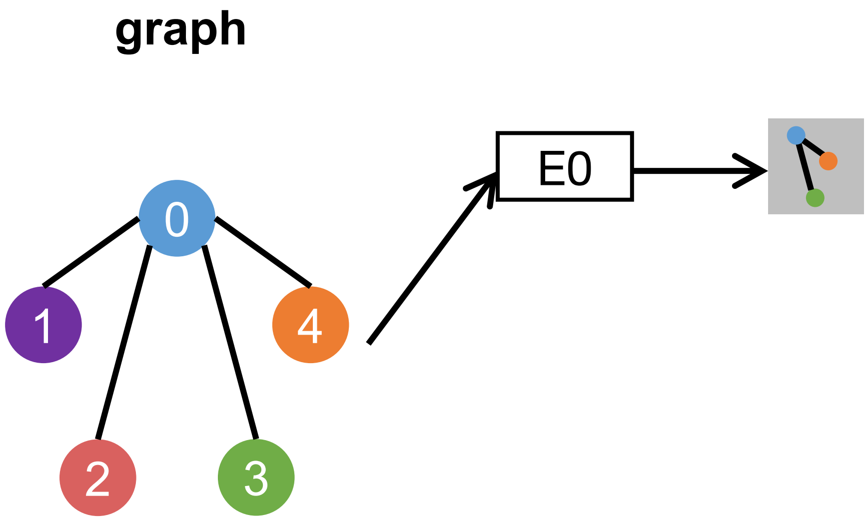

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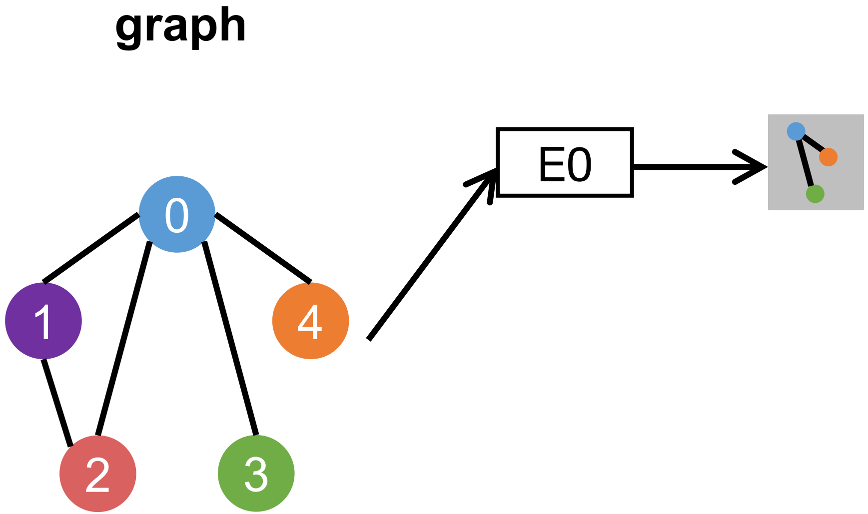

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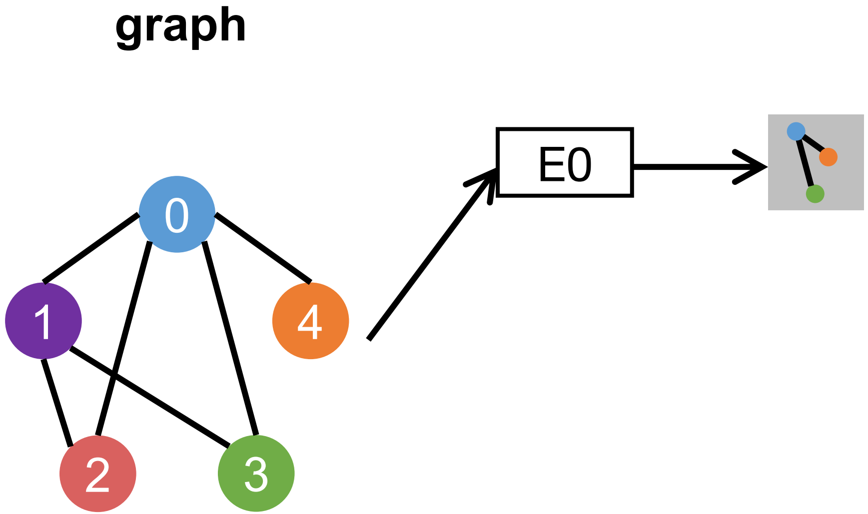

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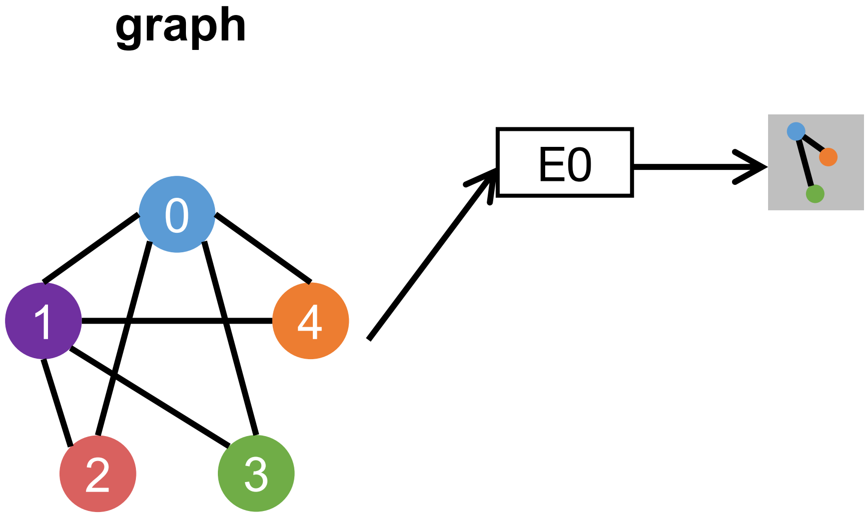

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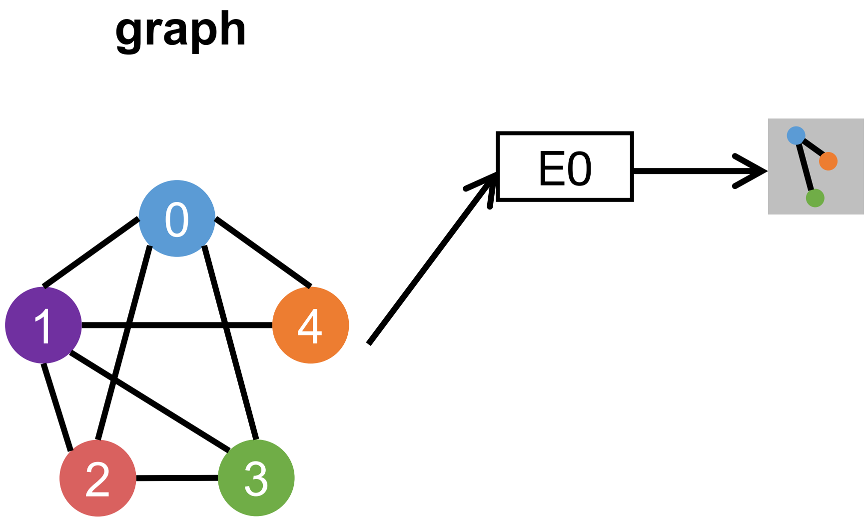

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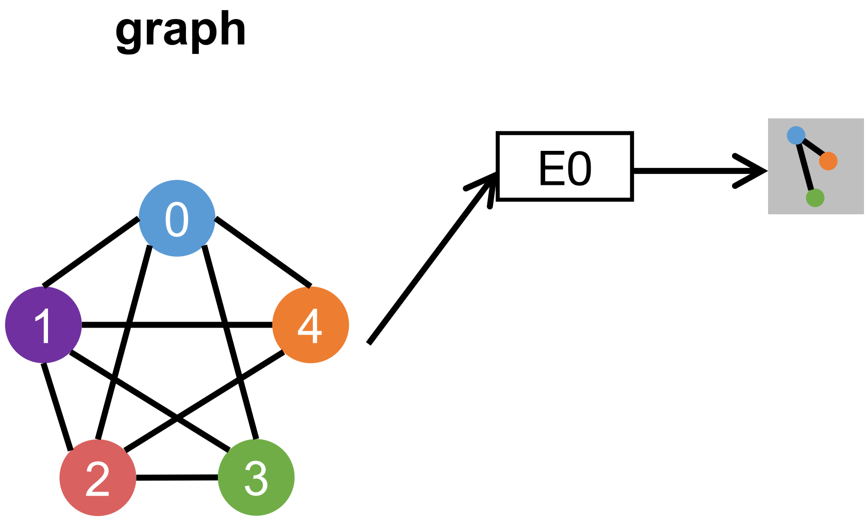

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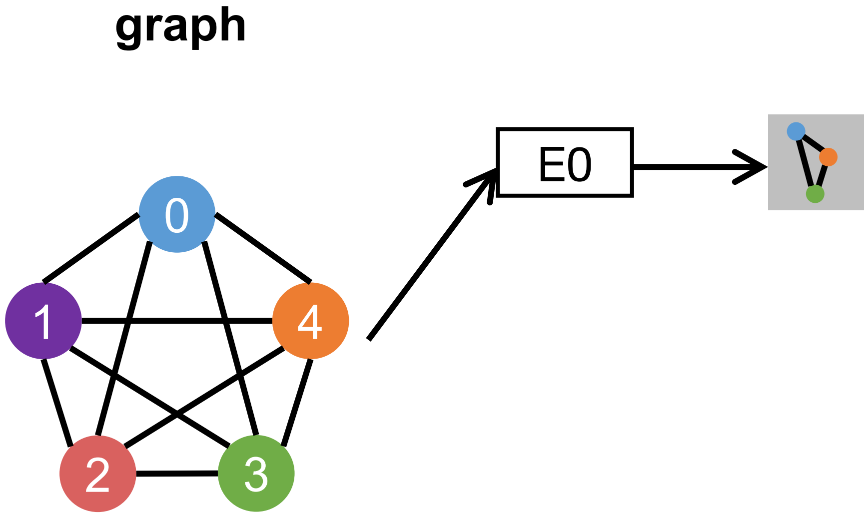

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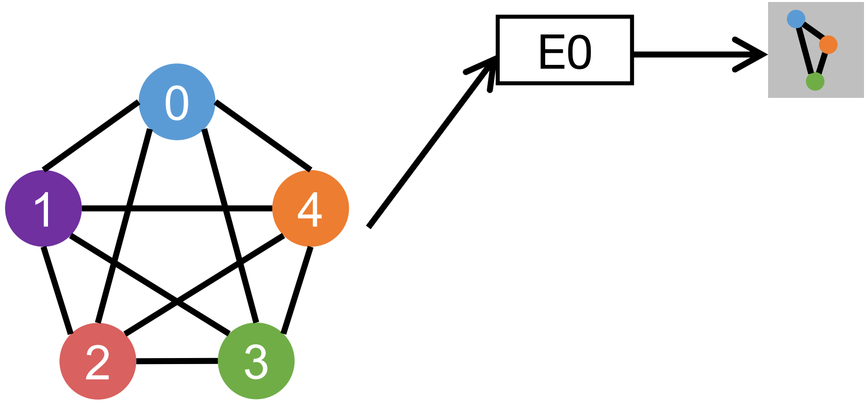
Approximation by Sampling Patterns

graph

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



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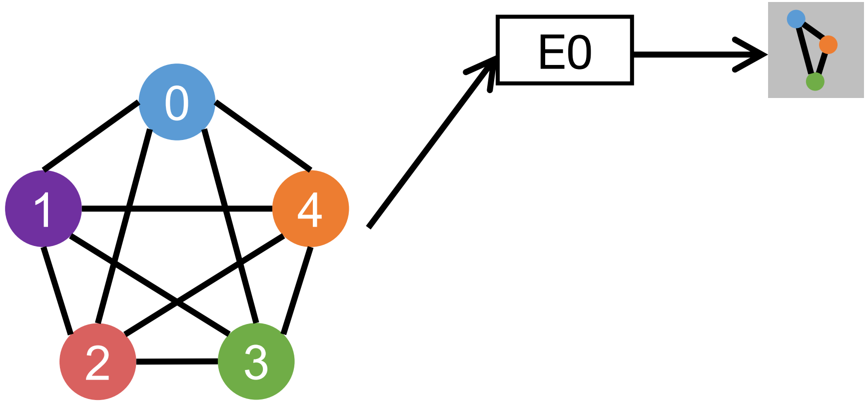

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$$e_0 = 40$$

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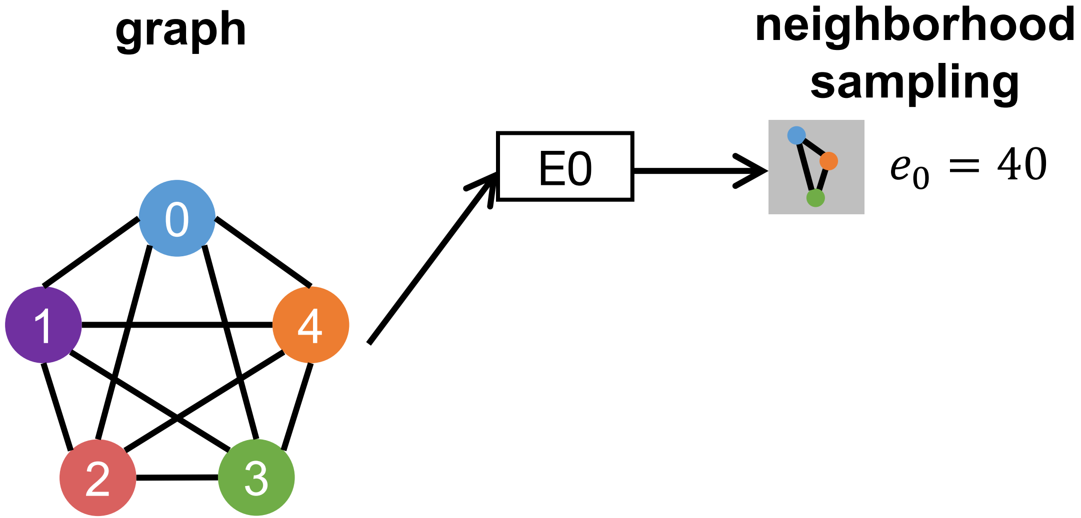

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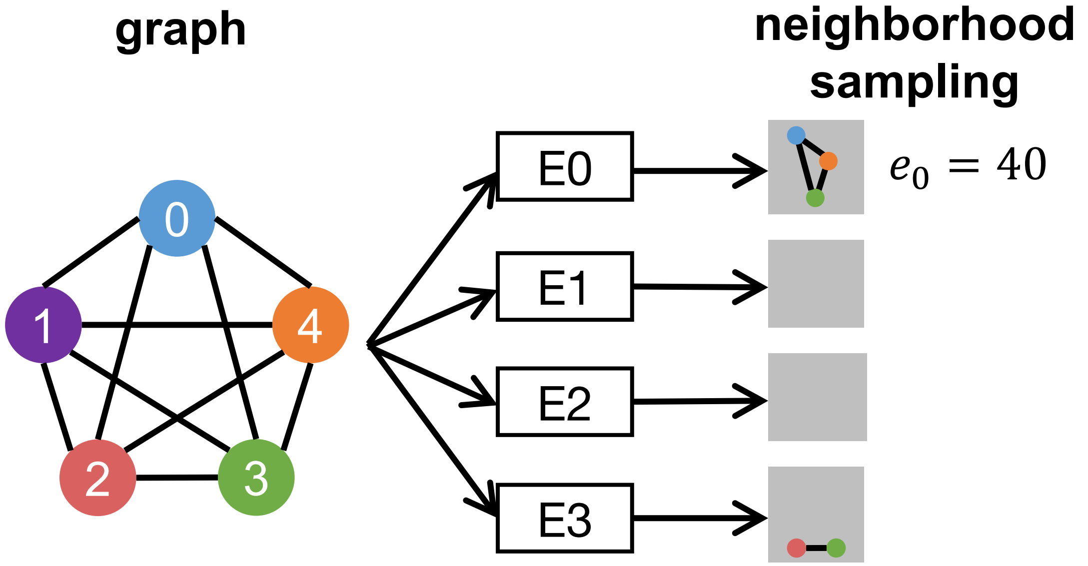

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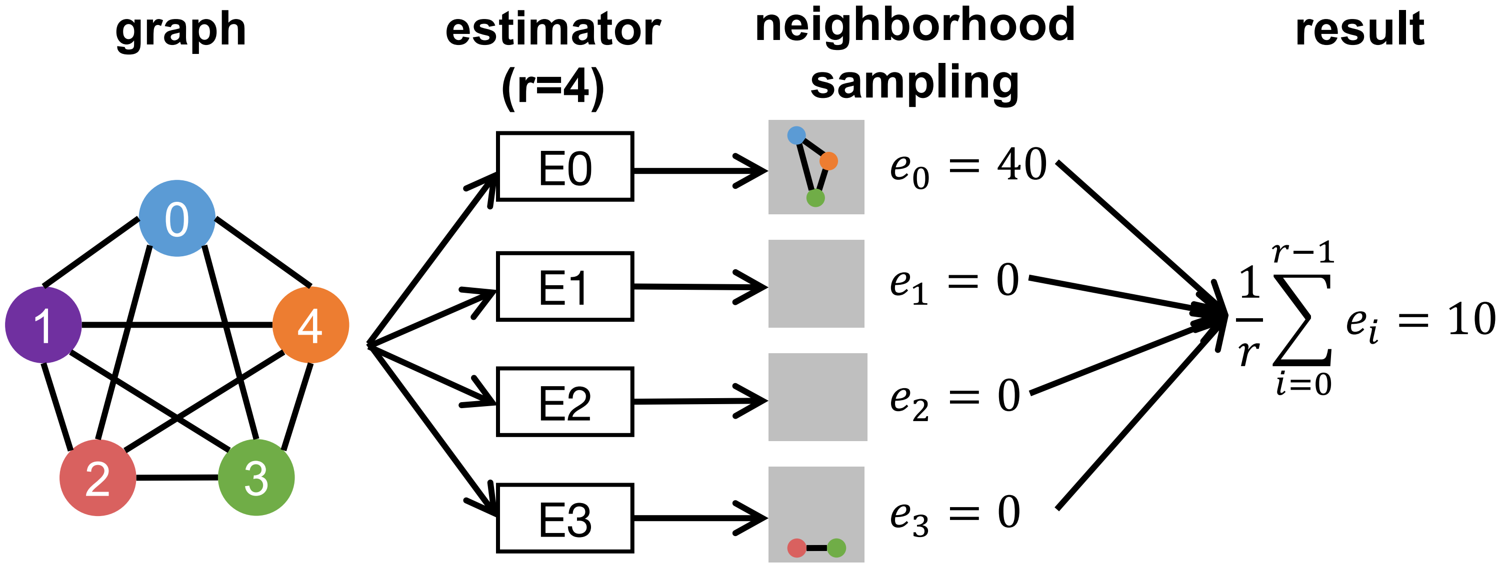

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Potential Benefits

- 16 node Apache Spark cluster
- Two graphs: Live Journal (68.9B), Twitter (1.47B)
- Count 3-Motifs (2 patterns: triangle, 3-chain)
- Set error to 5%

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Ours (5%)	16 x 8	LiveJ	4.8M	68.9B	11.5s
Arabesque	16 x 8	LiveJ	41.7M	1.47B	299.2s
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Building a General Purpose Approximate Graph Mining System

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General Patterns

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Distributed Settings

Building a General Purpose Approximate Graph Mining System

- General Patterns
- Distributed Settings
- Error Estimation

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- General Patterns
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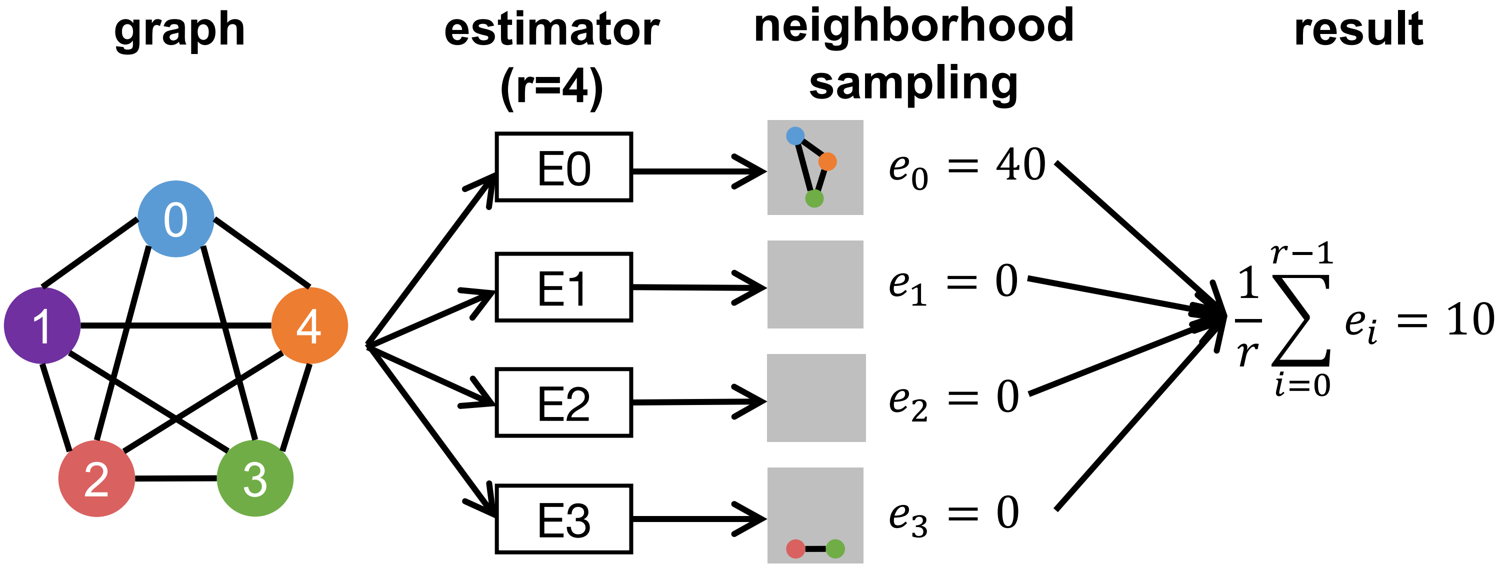
- Handling Updates

Challenge #1: General Patterns

<u>Problem:</u> Neighborhood sampling is for triangle counting

Break down neighborhood sampling into two phases:

- *Sampling* phase
- *Closing* phase



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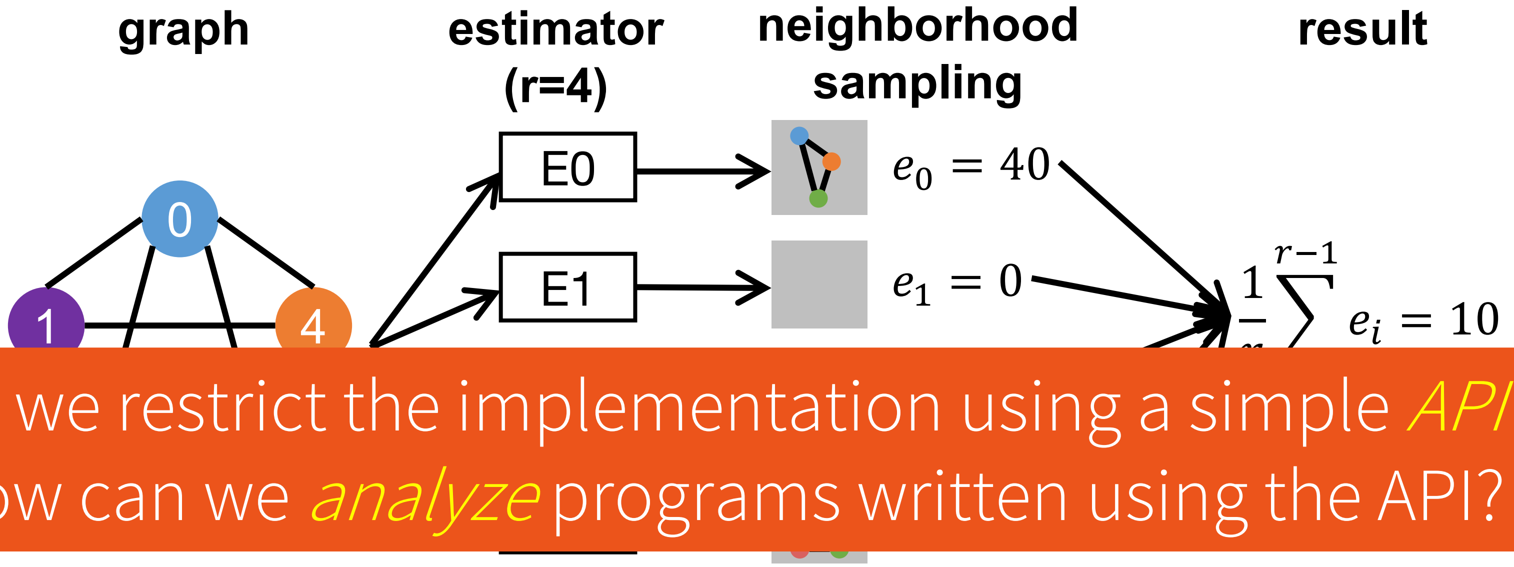

Can we restrict the implementation using a simple *API*?
How can we *analyze* programs written using the API?

Challenge #2: Distributed Setting

Problem: Neighborhood sampling is for a single machine

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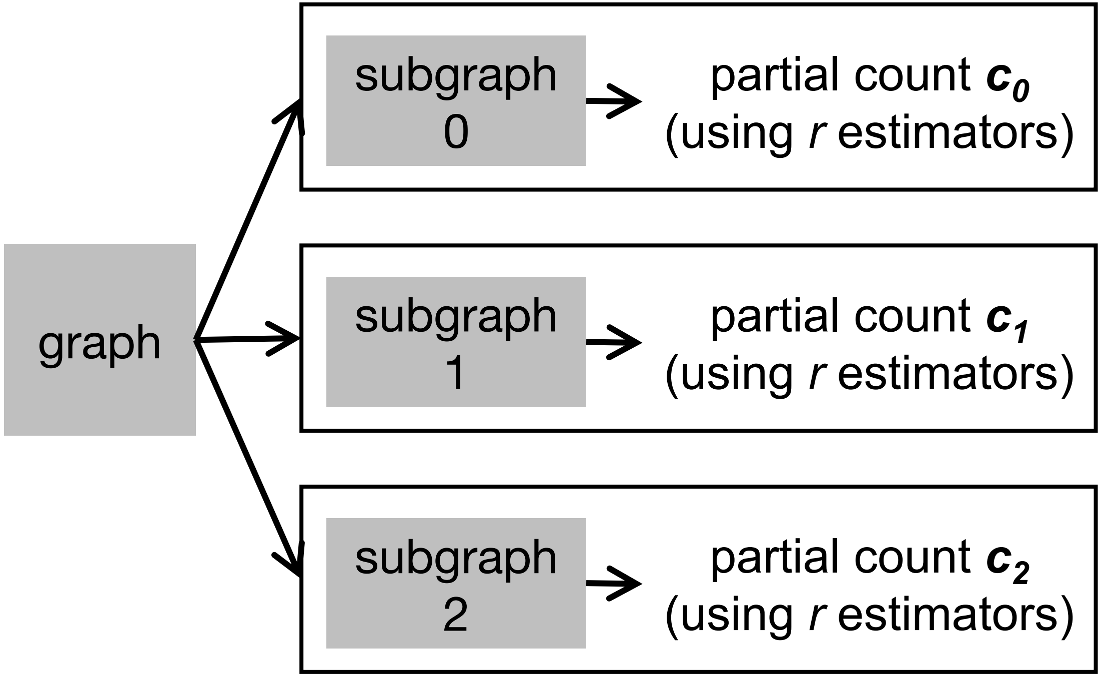
<u>Problem:</u> Neighborhood sampling is for a single machine

graph

Challenge #2: Distributed Setting

Problem: Neighborhood sampling is for a single machine



Challenge #2: Distributed Setting

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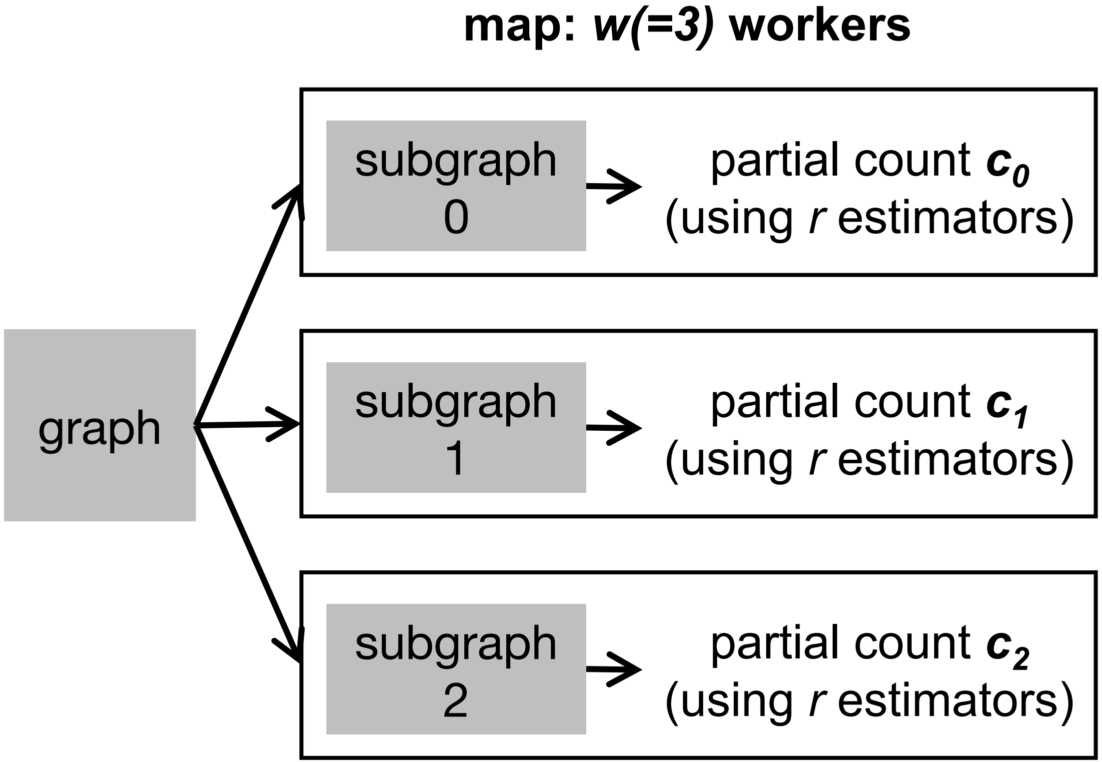

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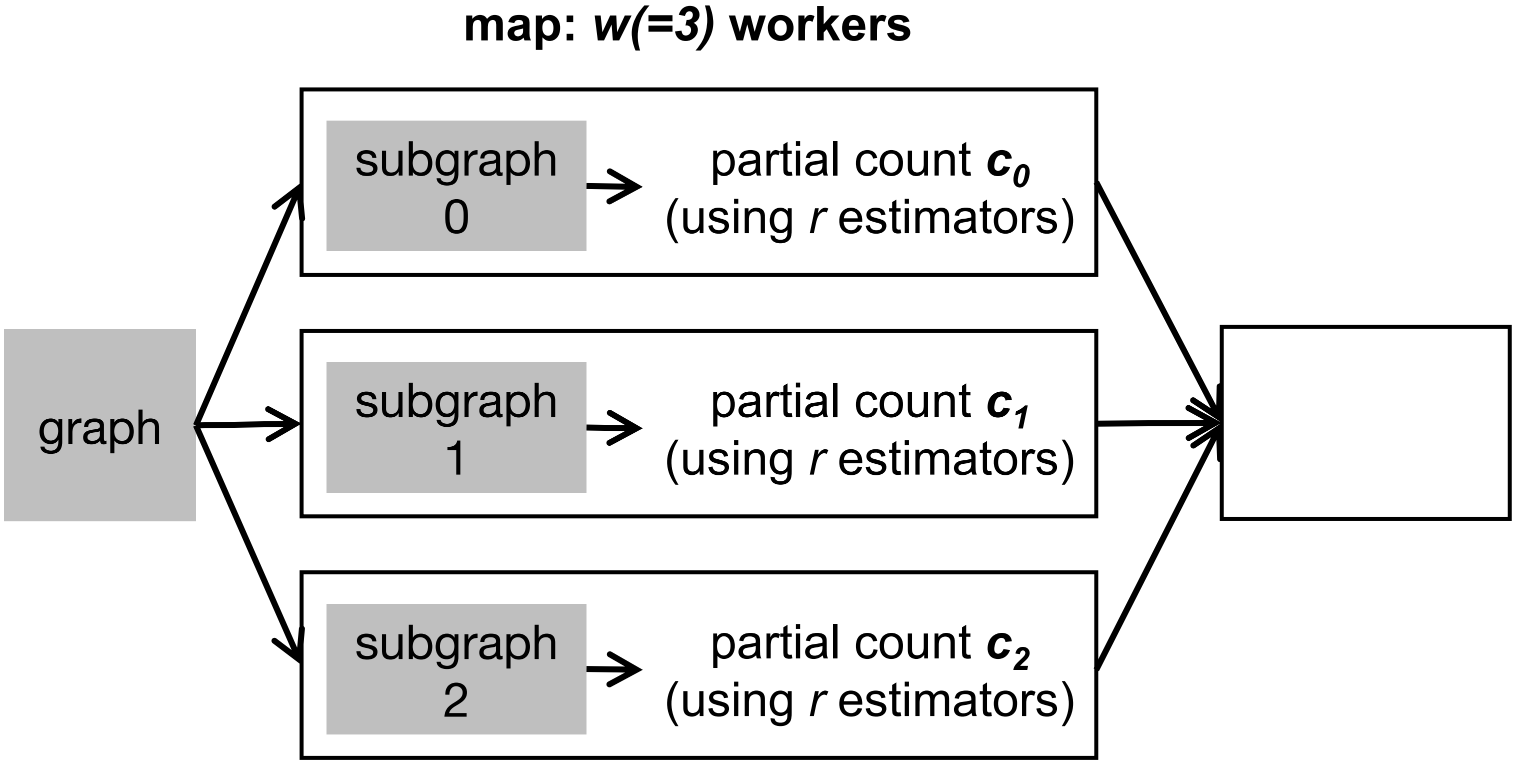

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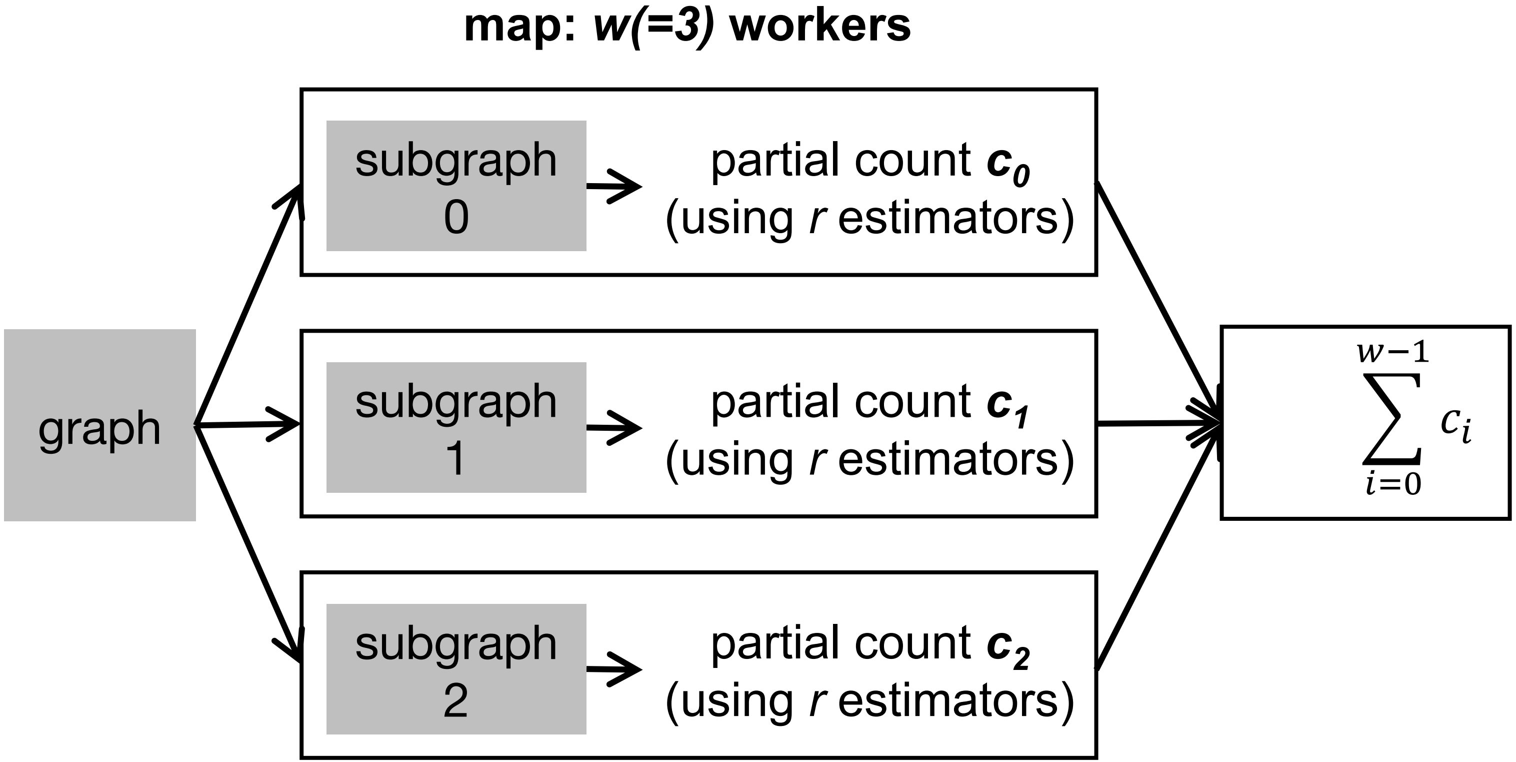

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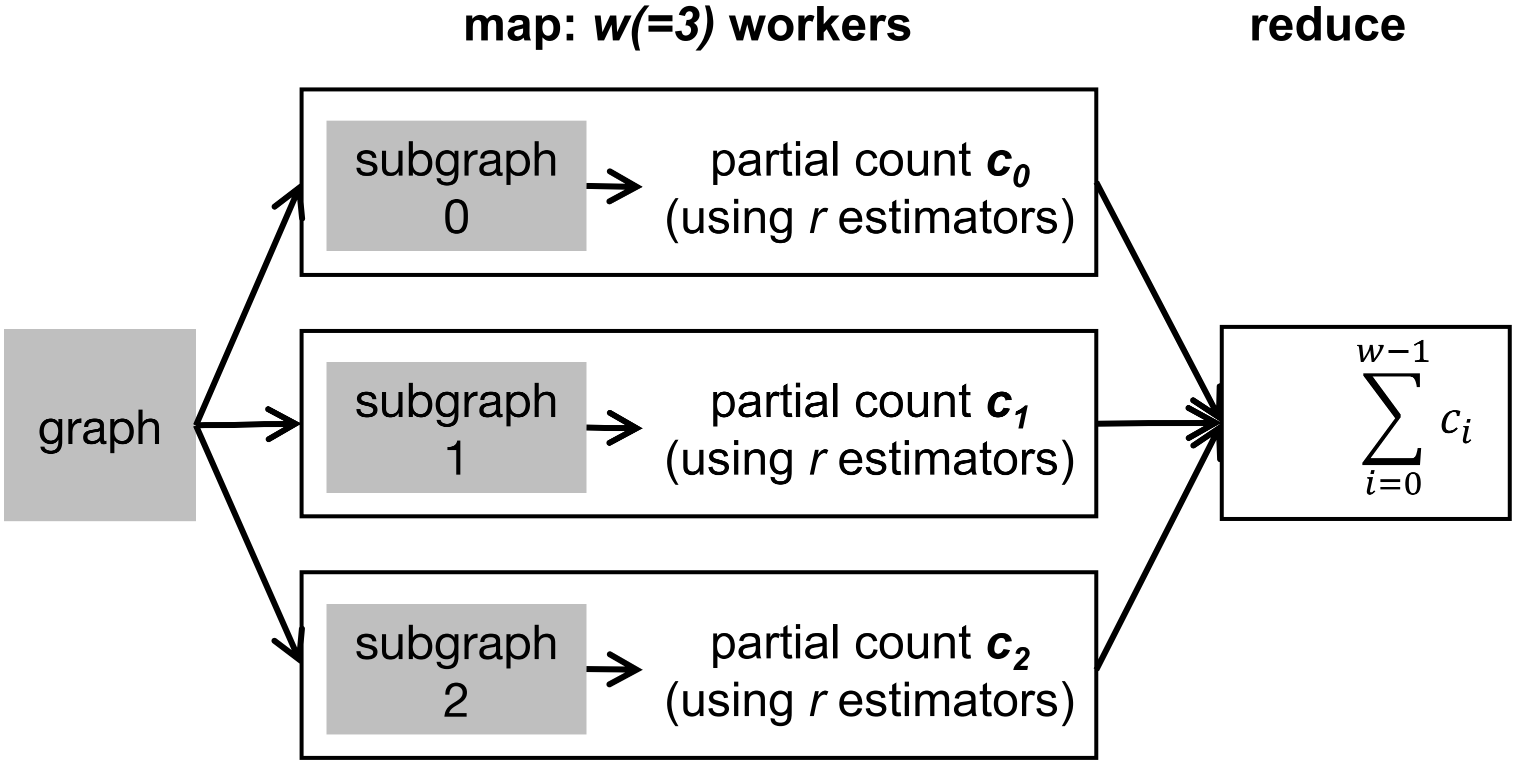

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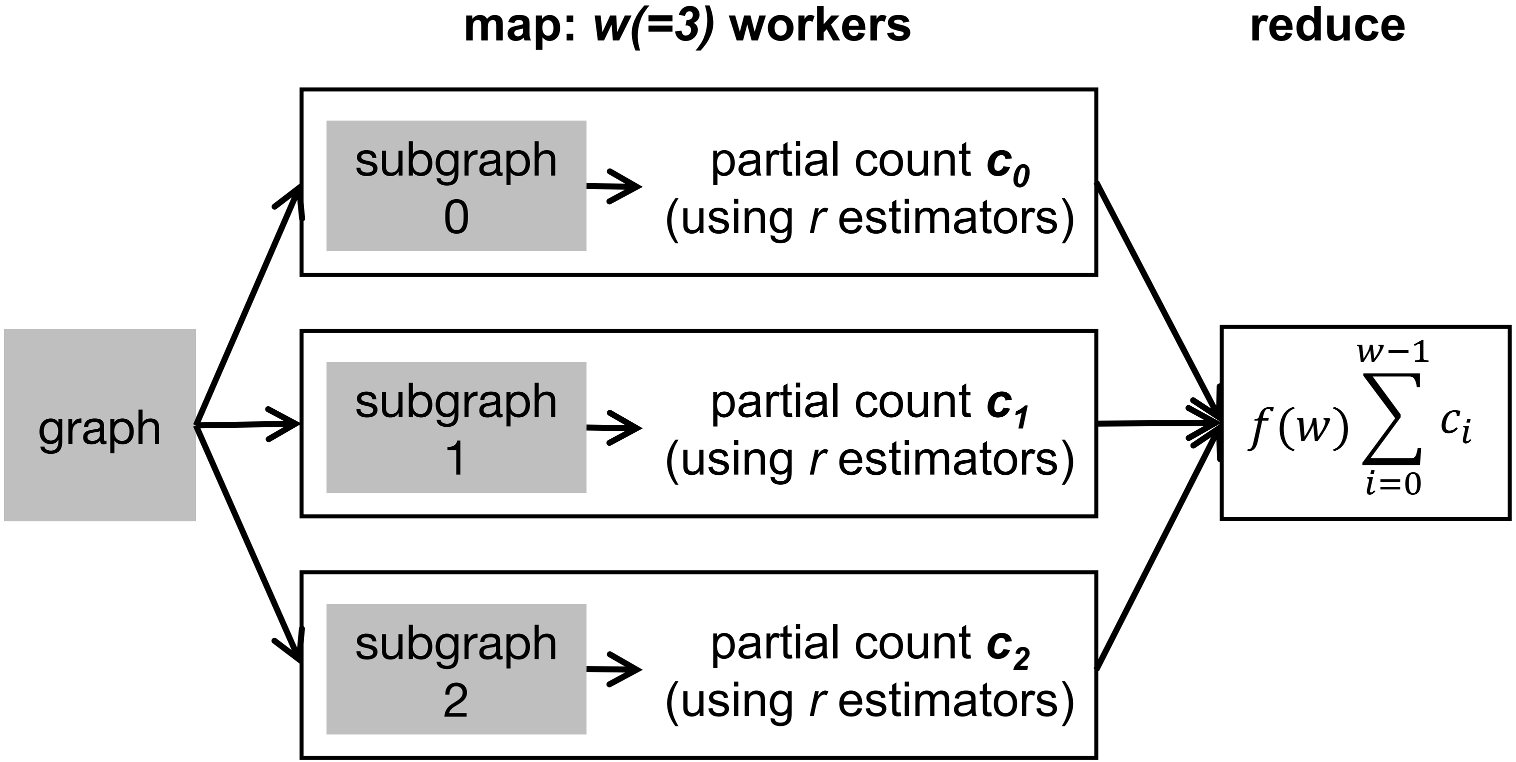

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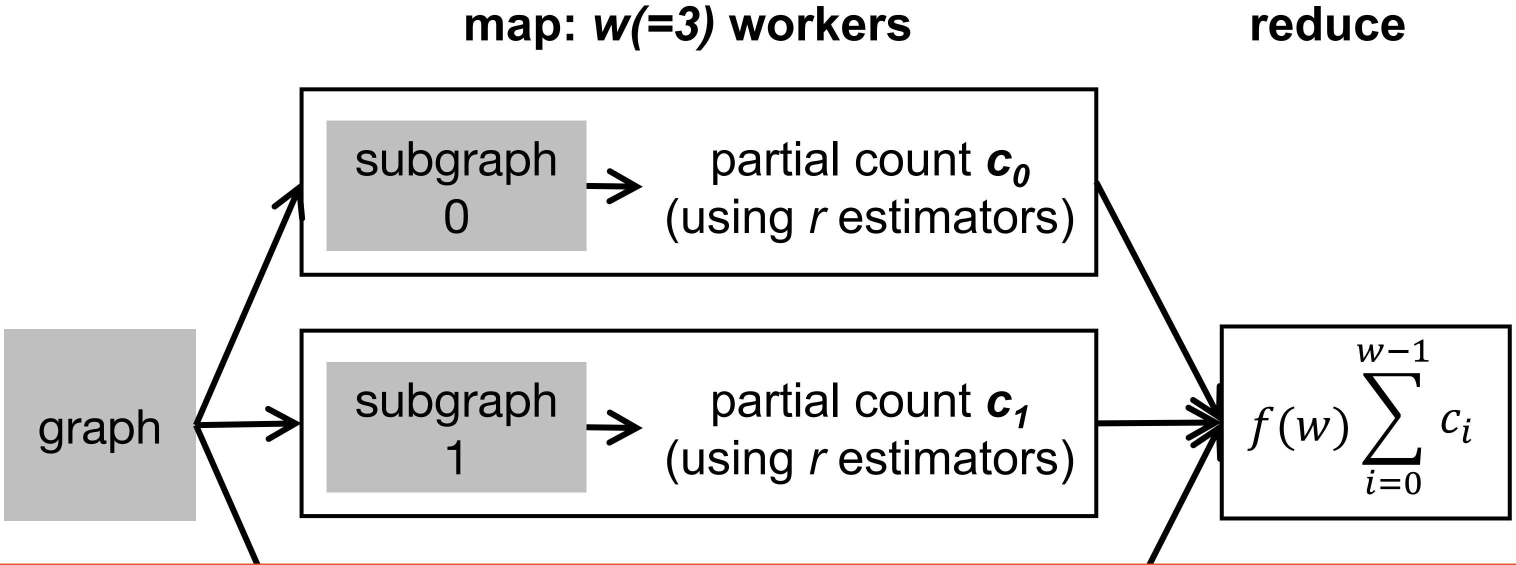


How do we compute *f(w)* for any pattern?
How does *f(w)* affect error?

Challenge #3: Building Error-Latency Profile

Problem: Given a time / error bound, how many estimators should we use?

Need to build two profiles:

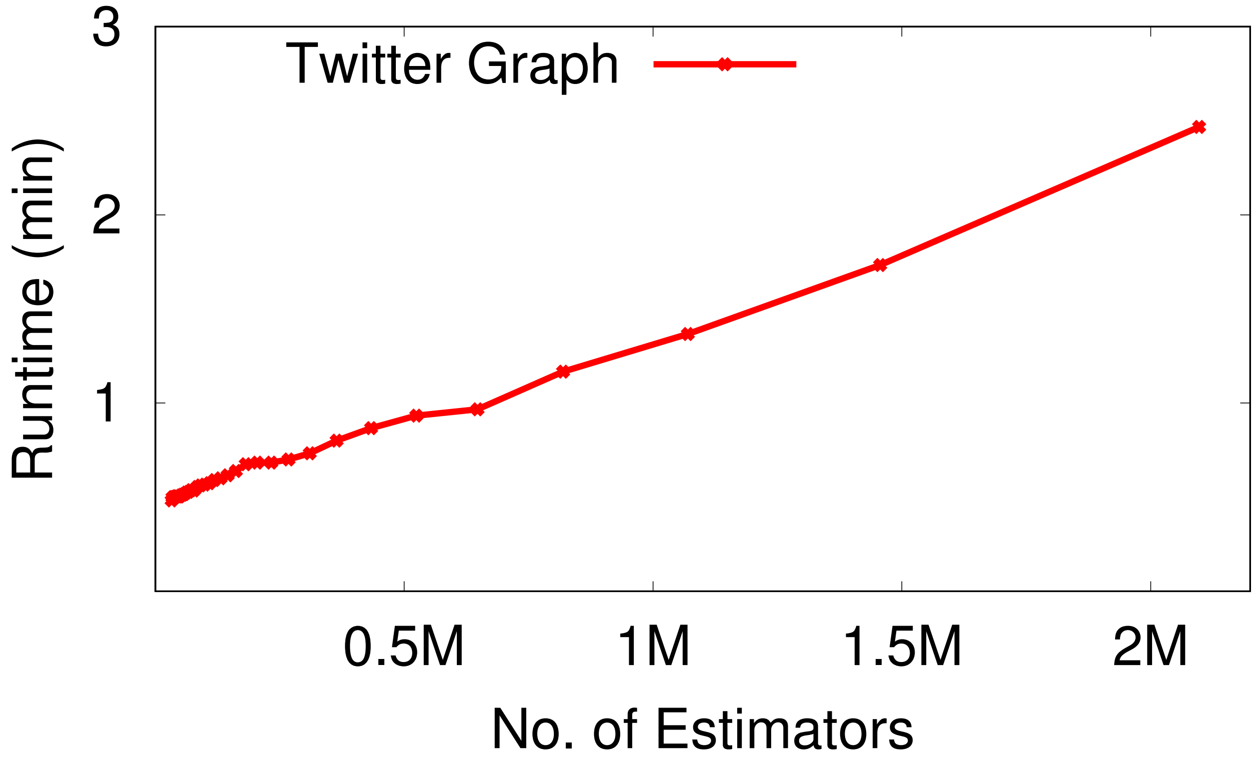
- Time vs #estimators
- Error vs #estimators

Naïve approach:

- Exhaustively run every possible point (infeasible)

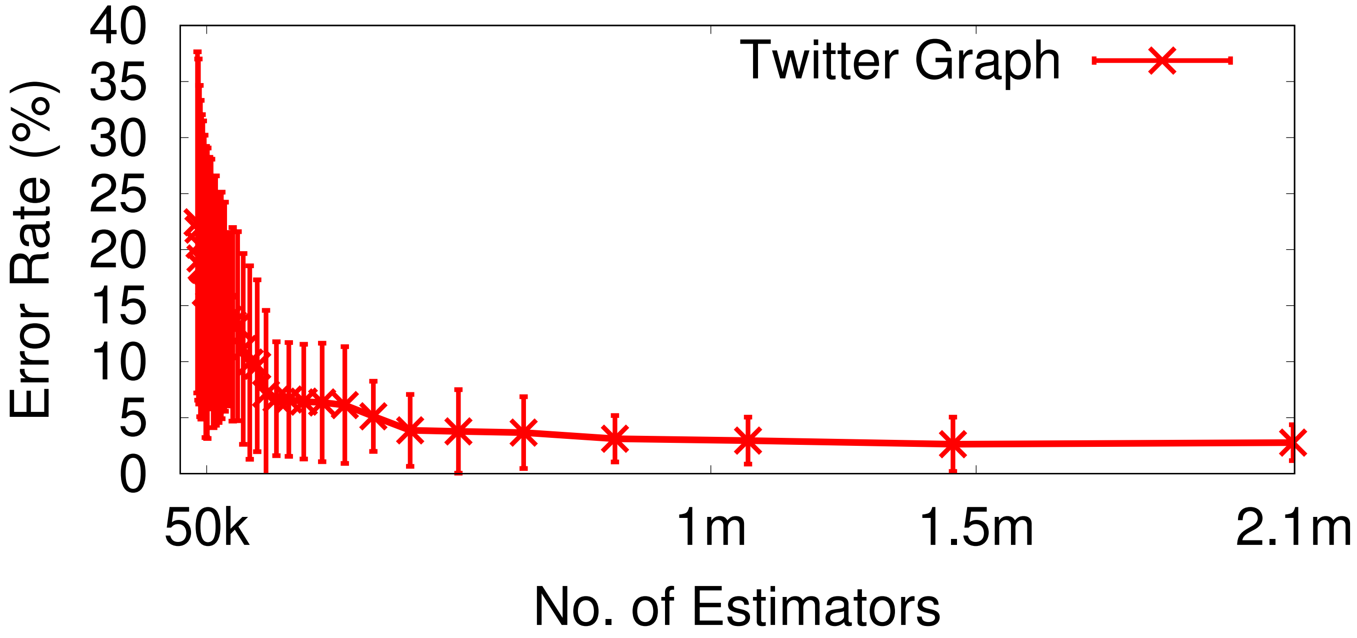
Building Estimators vs Time Profile

Time complexity linear in number of estimators



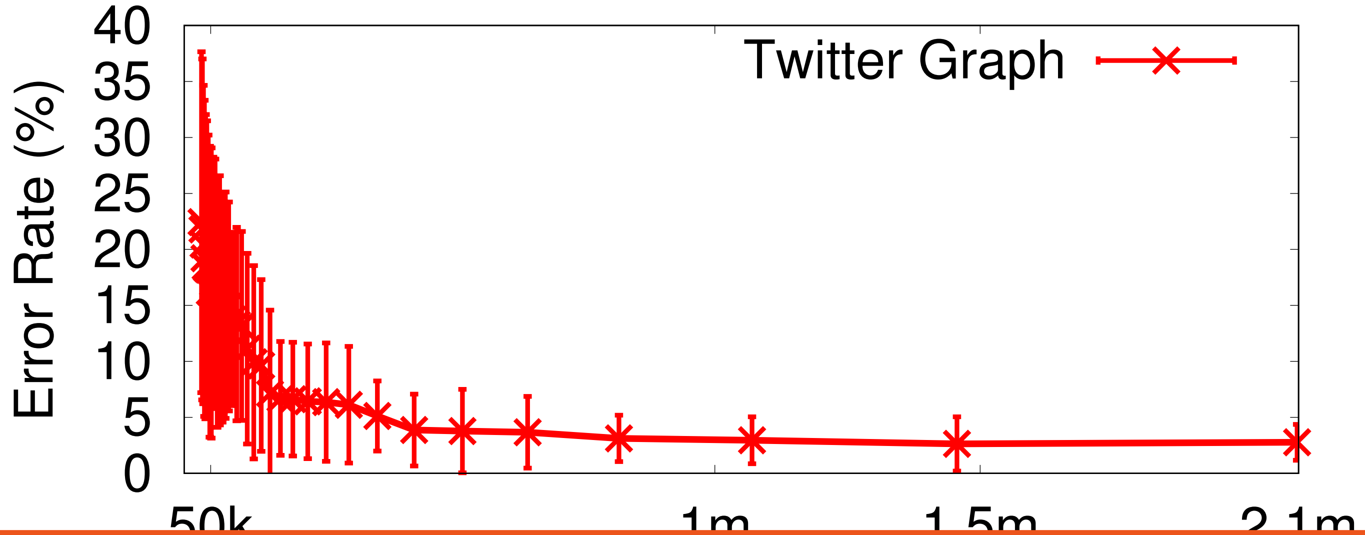
Building Estimators vs Error Profile

Error complexity non-linear in number of estimators



Building Estimators vs Error Profile

Error complexity non-linear in number of estimators



Leverage techniques like *experiment design/Bayesian optimization*?
How do we avoid the need to know the ground truth?

Challenge #4: Updates

Problem: Graphs and queries can be updated/refined

Several systems challenges:

- Incremental pattern mining
  - Can the error-latency profiles be updated?
- Caching
  - Re-use results
  - Pre-computation

Conclusion

- Approximation is a promising solution for pattern mining
  - Significant benefits, and can handle much larger graphs…
  - … but cannot output all instances of the pattern
- Several challenges in realizing it
  - How to extend the technique to general patterns?
  - How to do approximate pattern mining in a distributed setting?
  - How do we estimate the error?
  - How do we handle updates?

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

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