Distributed Evaluation of Subgraph Queries Using Worst-Case Optimal Low-Memory Dataflows

Khaled Ammar, Frank McSherry, Semih Salihoglu, Manas Joglekar

Presented by: Ramya Nagarajan
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Agenda

- Motivation
- Existing Approaches
- Dataflow Primitive
- Contributions
- Implementation
- Evaluation
- Further Work

Motivation

- Subgraph queries are a fundamental computation performed by many applications
  - Clique-finding for related page detection
  - Diamond-finding for social network recommendation systems
- Efficiency and scalability as primary goals
- Linear use of memory, worst-case optimal computation and communication costs

Contributions

- BigJoin
  - distributed algorithm for static graphs
  - Achieves a subset of theoretical guarantees
- Delta-BiGJoin:
  - Distributed algorithm for dynamic graphs
  - Achieves same theoretical guarantees in insertion-only workloads
- BigJoin-S:
  - Distributed algorithm for static graphs
  - Achieves all theoretical guarantees
  - Notable theoretical guarantee: balances work-load across distributed workers on arbitrary inputs instances

Existing Approaches

- Distributed Approaches:
  - Edge-at-a-time
  - Variants of Shares or Hypercube
- Serial Approaches:
  - Vertex-at-a-time

Edge-at-a Time Approaches

- Treat query subgraph as a relational query
- Execute series binary joins to determine result
- Provably worst suboptimal:
  - Worst-case $O(IN^2)$ computations

```
open-tri(a1,a2,a3):=edge(a1,a2),edge(a2,a3)
tri(a1,a2,a3):=open-tri(a1,a2,a3),edge(a3,a1)
```

Shares Algorithm

- Given a distributed cluster with w workers, n relations, m attributes (ie n edges, m vertices)
- Divides the output space equally over w workers
- Replicates edge tuples and distributes each tuple to every worker that can produce an output depending on tuple
- Workers run local join algorithm on received input
- Improved communication and computation costs
- Super-linear cumulative memory growth

Vertex-at-a-Time Approaches

- Generic Join:
  - Starts by finding all a1 vertices that will end up in output
  - Then (a1, a2), etc.

Generic Join Algorithm

- Global Attribute Ordering
- Extension Indices
  - $a_1 \ldots a_m$ subsets in queries
  - Maps to $j_1 \ldots j_m$ subset
- Prefix Extension Stages
  - Iteratively compute result of Q when each relation is restricted to the first j attributes in common global order

Dataflow Primitive

- Starts with a collection of P_j tuples stored across w workers
- Produces the P_{j+1} tuples across the same workers
- 4 steps:
    - Initialization
    - Count Minimization
    - Candidate Proposal
    - Intersection

Dataflow Primitive

- Initialization:
  - Tuples of P_j are distributed amongst workers arbitrarily
  - Each prefix transformed into a triple:
    - (prefix, smallest candidate set size, index of relation with that number of candidates)

Dataflow Primitive

- Count Minimization:
    - Workers exchange triples
    - Place each triple at the worker with access to the corresponding extension set
    - Each triple per worker updates its extension set
    - Final result if collection of triples indicating the prefix relations with the fewest extensions

Dataflow Primitive

- Candidate Proposal
  - Produce triple (p, min-c, min-i)
  - Each extension e of P
- Intersection
  - Workers exchange candidate tuples for each relation

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BiGJoin:
Joins on Static Relations

- Used for evaluating queries on static graphs
- Steps:
  - Arbitrarily order attributes
  - Build indices over each relation for each prefix in global order
  - Assemble dataflows for extending each P_j to P_{j+1} for each attribute a_i

BiGJoin Analysis

- O($mnMaxOut_Q$) communication and computation costs
  - Equal to GJ
- Cumulative Memory Required:
  - O(mIN + mB)
- Good work-load balance across workers
- No guaranteed workload balance on adversarial inputs

Delta-BiGJoin:
Joins on Dynamic Relations

- Delta-GJ Algorithm
  - Query Q
  - For each relation R, have some change to the deletion or addition of records in that relation
  - New delta query for each relation
    - Assume that tuples in record are labeled s.t can tell inserted records apart from existing records
  - Union of delta queries results in correct output query
  -

Delta-BigJoin

consider the following n delta queries:

$$
\begin{aligned}
dQ_1 &:= \Delta R_1, R_2, R_3, ..., R_n \\
dQ_2 &:= R_1', \Delta R_2, R_3, ..., R_n \\
dQ_3 &:= R_1', R_2', \Delta R_3, ..., R_n \\
&\cdots \\
dQ_n &:= R_1', R_2', R_3', ..., \Delta R_n
\end{aligned}
$$

Delta-BiGJoin Analysis

- Communication and computation cost: $O(mn^2 + MaxOut_Q)$
- Cumulative Memory: $O(mNIN(z) + mB)$
- Rounds of Computation: $O(^{(mn\text{^}2MaxOutQ)}/B') + zmn^2)$

BiGJoin-S

- Sources of Imbalance:
  - Sizes of extension indices
    - A single worker stores the entire extension set for a give prefix
  - Number of Proposals
    - Imbalanced amount of candidate extensions to prefixes
  - Number of Index Lookups
    - If many prefixes originate from the same relation R, there can be an imbalance in the number of prefixes and extensions each worker receives

BiGJoin-S

- Handling Skew
  - Skew-Resilient Indices
  - Modified Dataflow Primitive
    - Extension-Resolve
    - Intersect
    - Count
    - Balance

BiGJoin-S

- Skew-resilient Extension Indices
  - Split extension indices across workers
  - Count Index
  - Extension Resolver Index
  - Original Extension Index

BiGJoin-S

- Extension-Resolve
  - In Big-Join:
    - Pass (p, k) pair to extension resolver
    - Receive candidate extension in return
  - Skew in number of prefixes an extension has
  - Big-JoinS:
    - Locally aggregate extension requests made to a certain relation for a certain (p, k)
    - Send only one version of this request

BiGJoin-S

- Intersect
  - Big-Join:
    - Each (p, e) is routed through each of the Extension sets in order
  - Big-JoinS:
    - Distributed lookup of (p, e) by sending to the worker that holds the Extension set for (p, e)

BiGJoin-S

- Balance
  - Skew: Imbalance in the amount of work each worker receives after count minimization
  - Each worker deterministically distributes its amount of work amongst all workers

Theorem 3.4. *Suppose* $\frac{B'}{w} \geq \max\{w, \log(\mathrm{IN} \times MaxOut_Q)\}$ *and let* $B = wB'$. *Then BiGJoin-S has the following costs:*

- *Cumulative computation and communication cost of* $O(mnMaxOut_Q)$ *and memory cost of* $O(mn\mathrm{IN} + mB)$.
- $O(\frac{mnMaxOut_Q}{B})$ *rounds of computation.*
- *With at least probability* $1 - O(\frac{1}{\mathrm{IN}})$, *each worker performs* $O(B')$ *communication and computation in each round of the algorithm. In MPC terms, the load of BiGJoin-S is* $O(\frac{\mathrm{mnIN}}{w} + mB')$, *so assuming* $B' < \frac{IN}{w}$, *BiGJoin-S has optimal load.*

Evaluation

- Evaluate triangle finding on standard graphs on different systems
  - Establish a baseline for running time
- Implementation scaling
  - Vary number of workers across single machine and multiple machines
  - 64 billion-edge graph
- Evaluate BigJoin and Delta-BiGJoin
- Batch size of 10,000

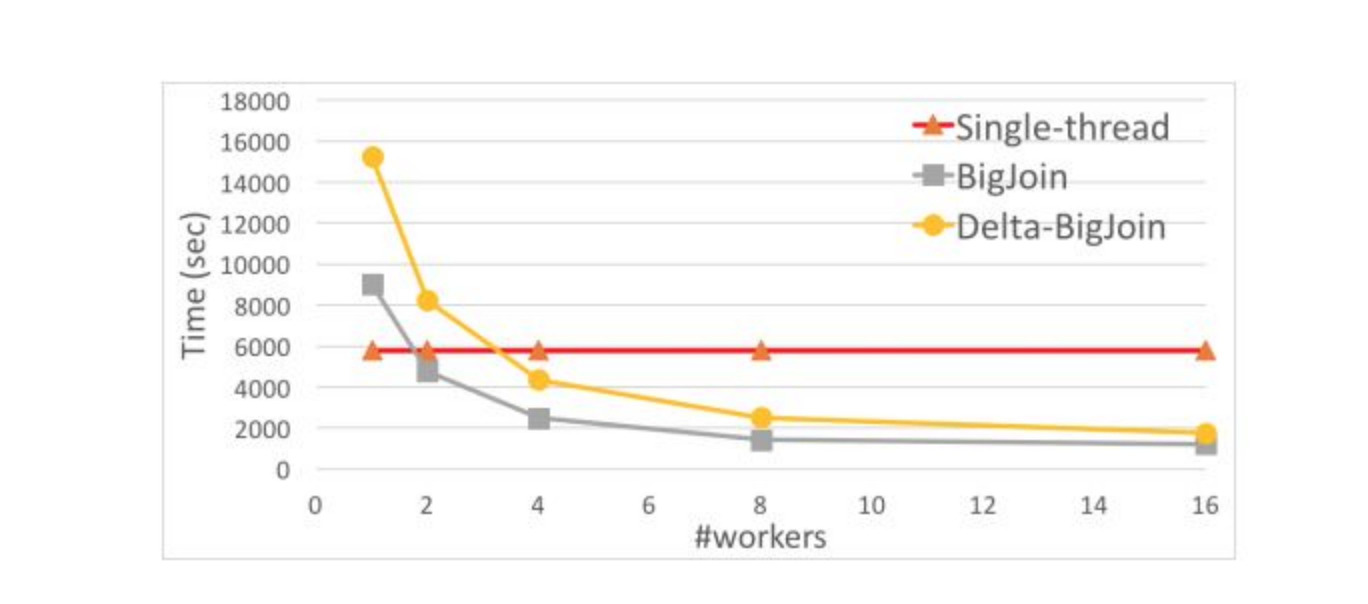
Experimental Setup

Table 1: Graph datasets used in our experiments.

Name	Vertices	Edges
LiveJournal (LJ) [36]	4.8M	68.9M
Twitter (TW) [35]	42M	1.5B
UK-2007 (UK) [35]	106M	3.7B
Common Crawl (CC) [60]	1.7B	64B

COST

- Number of cores that the algorithm needs to outperform an optimized single-threaded version



Evaluation against Frameworks

- EmptyHeaded
  - Highly-optimized shared-memory parallel system
  - Evaluating subgraph queries on static graphs using GJ

Query	EH-R	EH-I	BiGJoinT-R	BiGJoinT-I
Triangle-LJ	1.2s	150.3s	6.5s	1.9s
Diamond-LJ	31.7s	150.3s	712.3s	1.9s
Triangle-TW	213.8s	4155s	588s	34.4s

Evaluation against Frameworks

- Arabesque
  - Distributed system specialized in finding subgraphs

Query	Arbsq-R	Arbsq-I	BiGJoinT-R	BiGJoinT-I
Triangle	69.0s	1.46B	**3.4s**	**38M**
4-clique	273.7s	18.7B	**21.8s**	**350M**

Future Work

- Improving skew resilience of BigJoin
- Utilizing symmetries of queries
- Practical algorithms that have better than worst-case optimality