HUGE: An Efficient and Scalable Subgraph Enumeration System

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Outline

● Introduction

● The HUGE system
  ○ Advanced Execution Plan
  ○ The HUGE Compute Engine
  ○ DFS/BFS-adaptive Scheduler

● Experimental Evaluation

● Conclusion
Problem Definition

Subgraph Enumeration: Given a query graph $q$ and a data graph $G$ (both are undirected and unlabelled), the problem is to find all subgraph instances (matches) $g'$ in $G$, that are isomorphic to $q$.

Query Graph $q$

Data Graph $G$

Matches:
1.
2.
3.
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Matches:
1. $(u_0, u_1, u_2, u_3) \rightarrow (v_0, v_1, v_2, v_5)$
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3. $(u_0, u_1, u_2, u_3) \rightarrow (v_2, v_3, v_4, v_5)$
Existing Works

● **Join-based Algorithms**
  ○ Use distributed joins to compute matches (with different join algorithms and join orders)
  ○ *Push* data (intermediate results) from the host to remote machines
  ○ **High tension on both communication and memory usage**

● **Pull-based Algorithms**
  ○ *Pull* (and *cache*) the data graph instead to reduce communication volume and memory consumption
  ○ **May not reduce computation and communication time**
Initial Experiment - Setup

We conduct an initial experiment of representative existing works.

- **Dataset:**
  - Query Graph: Square
  - Data Graph: LiveJournal (4.8 million vertices, 43.4 million edges)

- **Algorithms:**
  - Join-based
    - SEED: Binary join algorithm with optimal bushy plan
    - BiGJoin: Worst-case optimal join algorithm
  - Pull-based
    - BENU: Store the data graph in external distributed key-value database and run backtracking (DFS) as in a single machine
    - RADS: Expand-star*-and-verify in a pulling manner

*Star: a tree of depth 1*
Initial Experiment - Results

<table>
<thead>
<tr>
<th>Comm. Mode</th>
<th>Work</th>
<th>Total Time (s)</th>
<th>Comp. Time (s)</th>
<th>Comm. Time (s)</th>
<th>Comm. Volume (GB)</th>
<th>Peak Mem (GB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pushing</td>
<td>SEED</td>
<td>1536.6</td>
<td>343.2</td>
<td>1193.4</td>
<td>537.2</td>
<td>42.3</td>
</tr>
<tr>
<td></td>
<td>BiGJoin</td>
<td>195.9</td>
<td>122.1</td>
<td>73.8</td>
<td>534.5</td>
<td>14.3</td>
</tr>
<tr>
<td>Pulling</td>
<td>BENU</td>
<td>4091.7</td>
<td>3763.2</td>
<td>328.5</td>
<td>25.3</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>RADS</td>
<td>2643.8</td>
<td>2478.7</td>
<td>165.1</td>
<td>452.7</td>
<td>19.2</td>
</tr>
<tr>
<td>Hybrid</td>
<td>HUGE</td>
<td>52.3</td>
<td>51.5</td>
<td>0.8</td>
<td>4.6</td>
<td>2.2</td>
</tr>
</tbody>
</table>

High communication volume and memory consumption
High external overhead and low utilisation
Sub-optimal plans

- Efficiency and scalability are jointly determined by:
  - Computation, Communication and Memory management
- None of the works achieves satisfactory performance for all three perspectives
Challenges

● Execution Plan
  ○ Previous works achieve “optimality” in a *specific* context
  ○ None can guarantee the best performance by all means

● Communication Mode
  ○ Non-trivial to make pull-based communication efficient
  ○ An efficient plan may require *both* pushing and pulling

● Scheduling Strategy
  ○ DFS strategy can lead to low hardware utilisation while BFS strategy has high memory demands
  ○ *Static heuristics* all lack in a tight bound and can sometimes perform poorly in practice
HUGE is a pushing/pulling-Hybrid SubGraph Enumeration system that features:

- **Advanced execution plan**
  - *Optimal* execution plan in a more *generic* context

- **Pushing/pulling-hybrid compute engine**
  - Efficiently support *both* push-based and pull-based communication

- **DFS/BFS-adaptive scheduler**
  - *Bounded-memory* execution without sacrificing computing efficiency
Advanced Execution Plan

- Break down an execution plan into **logical** and **physical** aspects
  - A unified logical join-based framework: $R(q) = R(q_1) \Join R(q_2) \Join \cdots \Join R(q_k)$
    - Join Unit: edges, stars, cliques
    - Join Order: left-deep, bushy
  - Physical join processing:
    - Join Algorithm: hash join, worst-case optimal (wco) join
    - Communication Mode: pushing, pulling
- Dynamic programming based optimiser to minimise both *communication* and *computation* in **generic** context
Example HUGE Plans

a. Plan for 4-clique

b. Plan for 5-path

All existing works can be readily plugged in to enjoy automatic performance improvement
HUGE Compute Engine

- Adopt the popular **dataflow model** for distributed execution
  - Execution plans are translated into dataflow graphs using different HUGE operators
- Pushing/pulling-hybrid **dual communication** mode
  - A new cache policy with two-stage execution strategy
- **Dynamic work stealing** for better load balancing
  - Two-layer intra- and inter- machine mechanism
System Architecture

- **RPC Server/Client**: Serve pulling requests
- **Router**: Pushes data to other machines
- **Worker**: Run de-facto computation
- **Cache**: HUGE’s LRBU cache
- **Scheduler**: HUGE’s DFS/BFS adaptive scheduler
LRBU Cache

- Two vital issues of traditional cache (e.g. LRU or LFU)
  - Memory copies
  - Locks
- Least recent-batch used (LRBU) cache
  - Target at a **zero-copy** and **lock-free** cache access
  - **Two-stage execution strategy**
    - **Fetch stage**: aggregate remote vertices, send async pull requests in bulk, and write remote vertices to the cache => **Write-only** (using single writer)
    - **Intersect stage**: read cache and compute intersections => **Read-only**
  - Synchronisation cost <7.5% with performance improvement 4.4x on average comparing with concurrent LRU
DFS/BFS-adaptive Scheduler

- Each dataflow operator is equipped with a **fixed-size output queue**
- Adopts **BFS-style** scheduling whenever possible to fully leverage parallelism
- Adapts dynamically to **DFS-style** scheduling if the output queue is full
Experimental Evaluation

- **Hardware:**
  - Local cluster: 10 machines with 4-core Intel Xeon E3-1220, 64G memory, 1TB Disk, connected on a 10Gbps network
  - AWS cluster: 16 AWS “r5.8xlarge instances” with 32 vCPUs, 256G memory, 1TB EBS storage, 10Gbps network *(for the web-scale experiments only)*

- **Datasets:**
  - 7 real-world data graphs, 8 queries selected from prior works

- **Others:**
  - Cache size: 30% of the data graph
  - Allow 3 hour maximum running time for each query
## Datasets

| Dataset      | |V|   | |E|   |
|--------------|-----|-----|-----|
| Google (GO)  | 875,713 | 4,322,051 |
| LiveJounal (LJ) | 4,847,571 | 43,369,619 |
| Orkut (OR)   | 3,072,441 | 117,185,083 |
| UK02 (UK)    | 18,520,486 | 298,113,762 |
| EU-road (EU) | 173,789,185 | 347,997,111 |
| Friendstar (FS) | 65,608,366 | 1,806,067,135 |
| ClueWeb12 (CW) | 978,409,098 | 42,574,107,469 |

### a. Table of Data Graphs

### b. Query Graphs
Speed Up Existing Algorithms (on LJ)

- **HUGE-BENU**
  - (sec) $2^{14}$
  - q1: 18x
  - q2: 49x

- **HUGE-RADS**
  - (sec) $2^{14}$
  - q1: 8.5x
  - q2: 4.8x

- **HUGE-SEED**
  - (sec) $2^{14}$
  - q1: INFx
  - q2: 3.5x

- **HUGE-WCO**
  - Out of Memory

Additional notes:
- BENU
- RADS
- SEED
- BiGJoin
- HUGE
All-Round Comparisons

- **q₁**

- **q₂**

- **q₃**

- **q₄**

- **q₅**

- **q₆**
Scalability

- Vary Number of Machines (on FS)

- Web-scale Graph (on CW)

<table>
<thead>
<tr>
<th></th>
<th>$q_1$</th>
<th>$q_2$</th>
<th>$q_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Throughput</td>
<td>2,895,179,286/s</td>
<td>354,507,087,789/s</td>
<td>206,696,071/s</td>
</tr>
</tbody>
</table>
Conclusion

- HUGE is an efficient and scalable subgraph enumeration system in the distributed context.
- HUGE is designed to be flexible for extending more functionalities such as:
  - Cypher-based Distributed Graph Databases
  - Graph Pattern Mining (GPM) Systems
  - Shortest Path & Hop-constrained Path
Thanks!