Distributed Set Reachability

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Germany

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Distributed Set Reachability

Distributed Set Reachability (DSR) is a generalization of graph reachability problem

- extended to sets
- in a distributed setting

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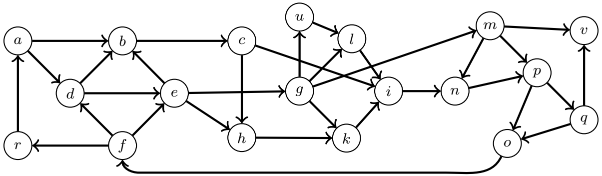

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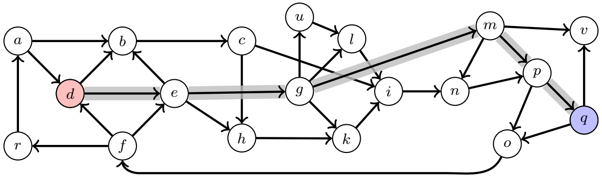

Graph G

$d \rightsquigarrow q$: True

- **Reachability.** $s \rightsquigarrow t$, find if there exists a path from s to t in G [SABW13, YCZ10]

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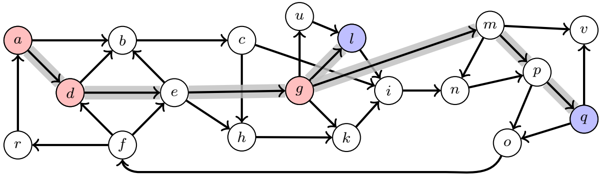

Graph G

Reachable pairs

$\langle a, l\rangle, \langle a, q\rangle$
$\langle d, l\rangle, \langle d, q\rangle$
$\langle g, l\rangle, \langle g, q\rangle$

- **Reachability.** $s \rightsquigarrow t$, find if there exists a path from s to t in G [SABW13, YCZ10]
- **Set Reachability.** $S \rightsquigarrow T$, finds all pairs $\langle s, t\rangle$, such that $s \in S$, $t \in T$ and $s \rightsquigarrow t$ in G [TKC+14, GA13]

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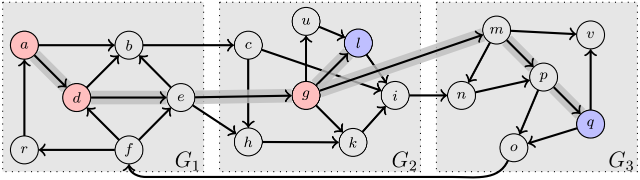

Graph G is partitioned into G_1, G_2, G_3

Reachable pairs

$\langle a, l\rangle, \langle a, q\rangle$

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- **Distributed Reachability.** $s \rightsquigarrow t$, find if there exists a path from s to t in G [FWW12]
- **Distributed Set Reachability.** $S \rightsquigarrow T$, finds all pairs $\langle s, t\rangle$, such that $s \in S$, $t \in T$ and $s \rightsquigarrow t$ in G [?]

Applications

Application 1: SPARQL 1.1 property paths processing on knowledge graphs

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Set Reachability Query:
$\textcolor{red}{Cities} \rightsquigarrow \textcolor{blue}{Countries}$

Applications

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- Example: How billionaries and philanthropic organizations are connected

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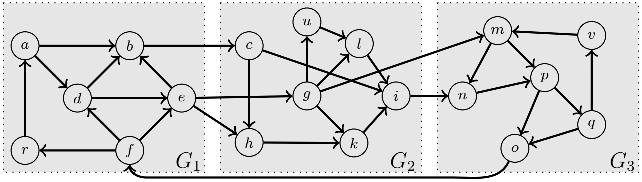
$Billionaries \rightsquigarrow Organizations$

How to solve a DSR query?

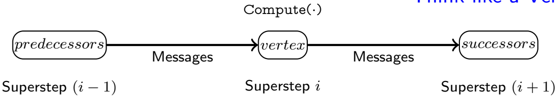
Query: $\{a, d, g\} \rightsquigarrow \{l, q\}$



How to solve a DSR query?

Vertex-Centric approaches: Like Pregel, Giraph,...

"Think like a Vertex"



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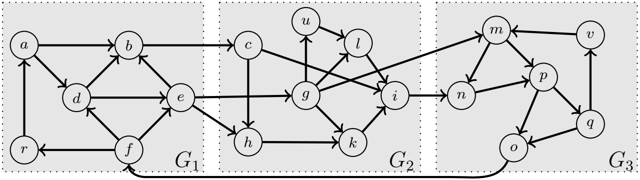

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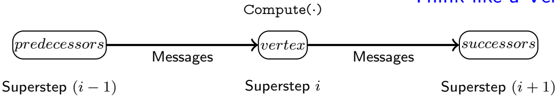

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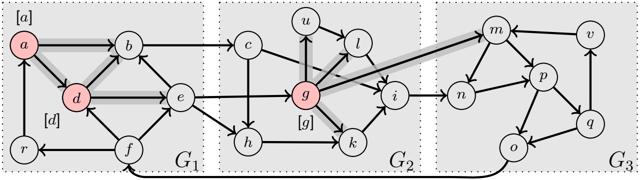
Supersteps

1



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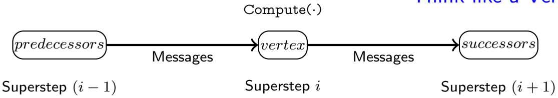

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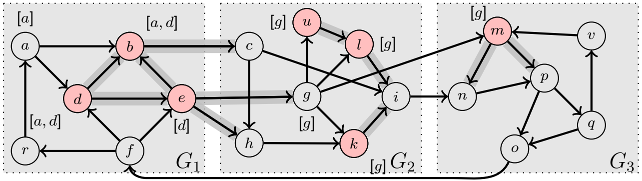
1

2



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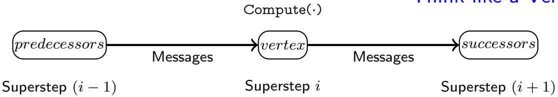

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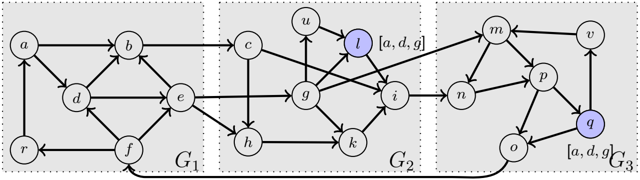
⋮

d



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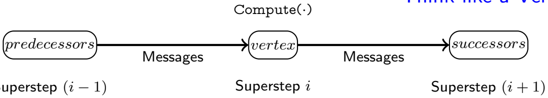

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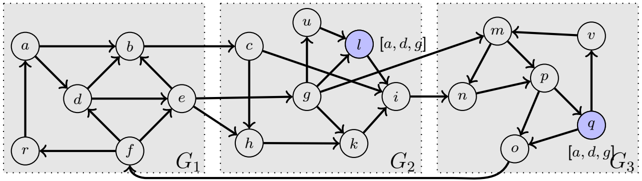

Perfomance: On small graphs ($\leq$ 10Mi edges) and query with $|S| = 10$ and $|T| = 10$

Dataset	Time(in sec)	Supersteps	Comm. Size(MB)
NotreDame	94.8	70	35.2
Stanford	341.9	267	79.1

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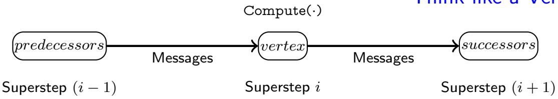

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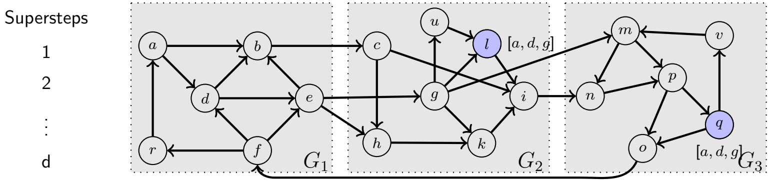

Challenges:

- no reuse of computations & no support for local indexes
- leading to many iterations ($\leq$ diameter)
- and thus high communication costs and high query processing times

An efficient solution for DSR?

Objectives:

1. minimize the size and number of messages exchanged
2. to speed up & reuse computations as much as possible in local nodes
3. scalable to large graphs

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   - reachability is invariant between supersteps
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2. **to speed up & reuse computations as much as possible in local nodes**
   - local graph + boundary graph ⇒ **Compound graph**
   - on the compound graph,
     build indexes via centralized (set) reachability approaches
     [YCZ10, SABW13, GA13, TKC+14]
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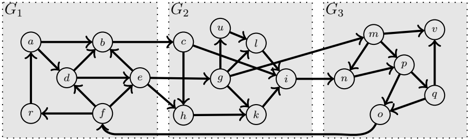
3. **scalable to large graphs**
   - boundary graph compression via equivalence sets grouping
   - condense compound graphs by computing SCCs

Precomputation



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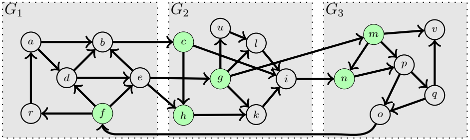

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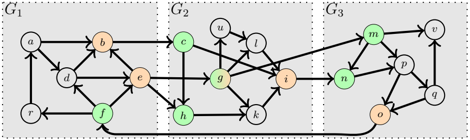

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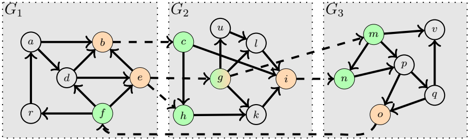

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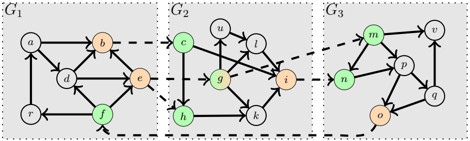

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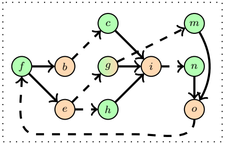
Step 1: Compute reachability from $I_i \rightsquigarrow O_i$ (set reachability) **(Boundary Graph)**



Boundary Graph

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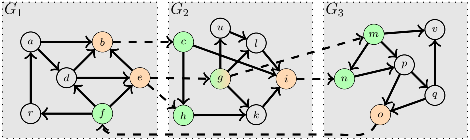

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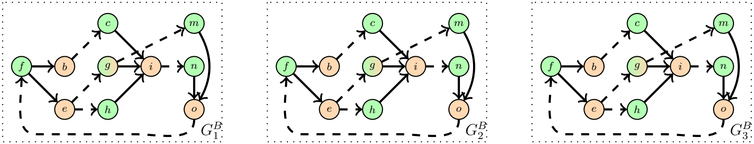

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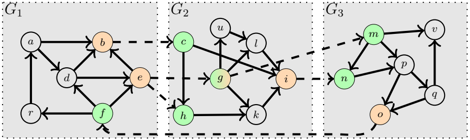

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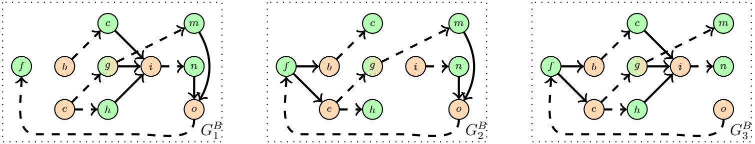

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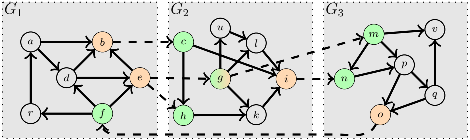

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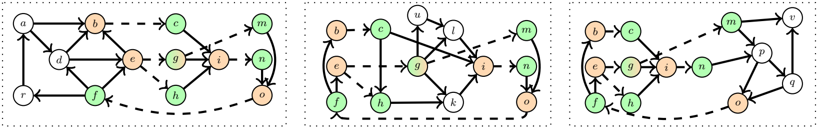

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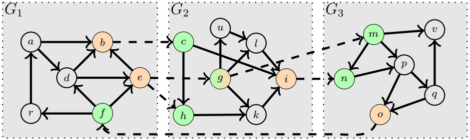

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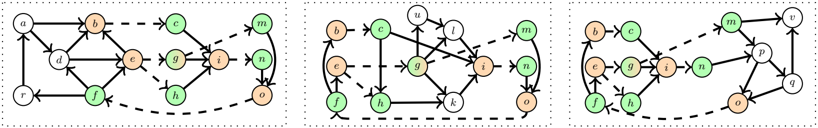
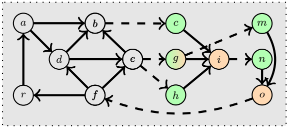
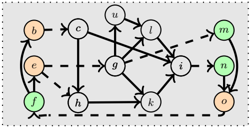
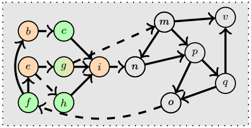


Step 3: Optionally, build local indexes to reuse computations and speed up query processing

Query processing







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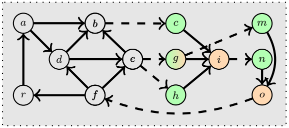
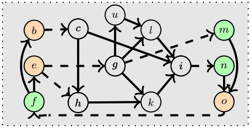


Forward List: $F_1 = \{c, g, h, m, n\}$
Backward List: $B_1 = \{g, i, o\}$



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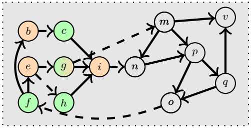

$F_3 = \{f, c, g, h\}$
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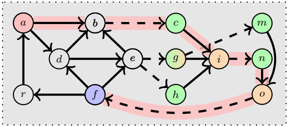
Query processing

Query: $a \rightsquigarrow f$



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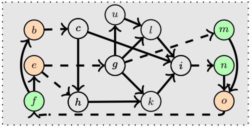

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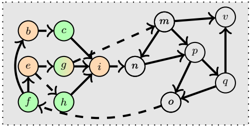

$F_3 = \{f, c, g, h\}$

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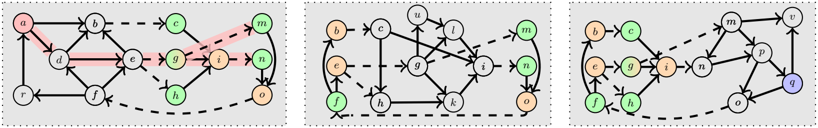
If s and t are local $\Rightarrow$ no communication, entire query can be processed locally

Query processing

Query: $a \rightsquigarrow q$



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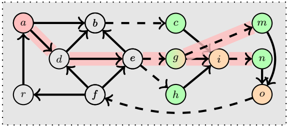
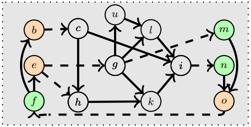
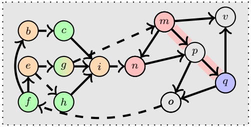






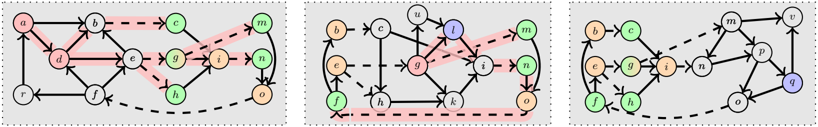
Forward List: $F_1 = \{c, g, h, m, n\}$ $F_2 = \{f, m, n\}$ $F_3 = \{f, c, g, h\}$

Backward List: $B_1 = \{g, i, o\}$ $B_2 = \{b, e, o\}$ $B_3 = \{b, e, i, g\}$

If s and t are non-local $\Rightarrow$ one step communication, involves atmost two partitions

Query processing

Query: $\{a, d, g\} \rightsquigarrow \{l, q\}$



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Step1: $\emptyset$ $\quad \{\langle g, l\rangle\}$ $\quad \emptyset$

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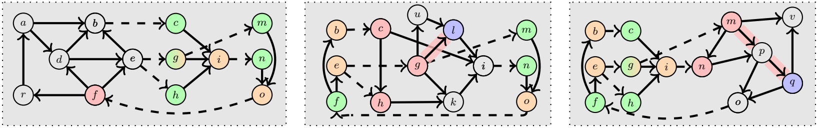
Query: $\{a, d, g\} \rightsquigarrow \{l, q\}$



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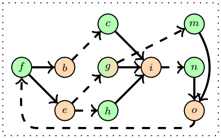
Step1:	$\emptyset$	$\{\langle g, l\rangle\}$	$\emptyset$
Step2:	$\emptyset$	$\{\langle a, l\rangle, \langle d, l\rangle\}$	$\{\langle a, q\rangle, \langle d, q\rangle\ \langle g, q\rangle\}$

Scaling to Large Graphs

One of the main challenges for scalability is the size of boundary graph



Boundary Graph

Size: $\mathcal{O}(\sum_{i=1}^{k}(|I_i| \cdot |O_i|) + |E_C|)$

Google: 43.6Mi $(8.5 \times |E|)$
LiveJ-20M: 861.4Mi $(43.07 \times |E|)$

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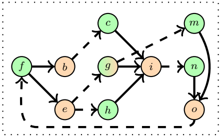

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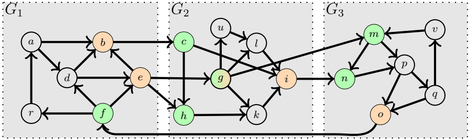

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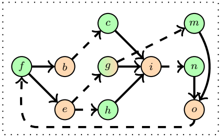

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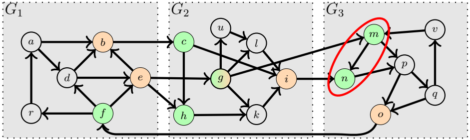

in-boundaries m, n reach same set of vertices in $G_3 \Rightarrow$ forward equivalent

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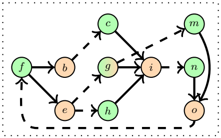

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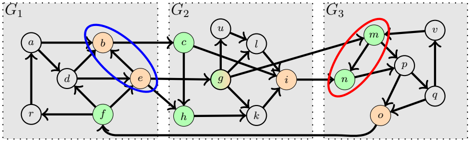

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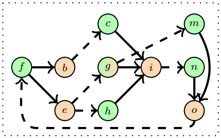

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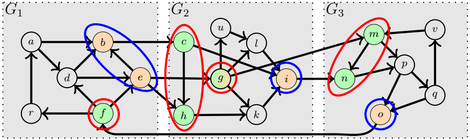

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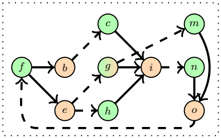

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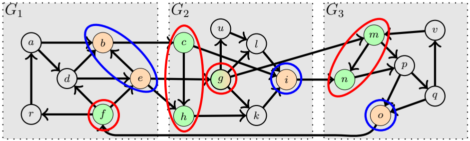

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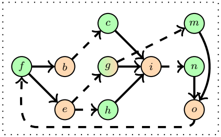

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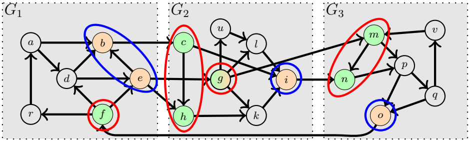

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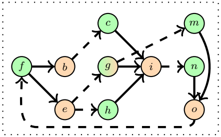

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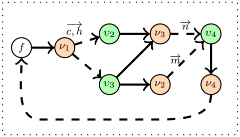

Compressed Boundary Graph

Size: $\mathcal{O}(\sum_{i=1}^{k}(|N_i| \cdot |\Upsilon_i|) + |E'_C|)$

N_i: set of in-virtual nodes at i

Υ_i: set of out-virtual nodes at i

$N_i \leq I_i$, $\Upsilon_i \leq O_i$, and $|E'_C| \leq |E_C|$

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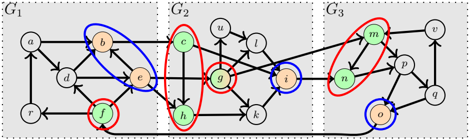

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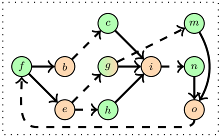

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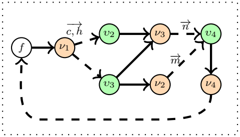

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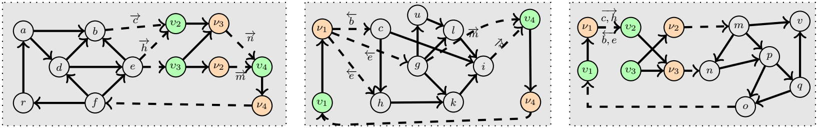

lower communication costs, scalable to very large graphs

Evaluation

Datasets:

Small Graphs	|V|	|E|	Large Graphs	|V|	|E|
Amazon	403,394	3,387,388	LiveJ-68M	4,847,571	68,993,773
BerkStan	685,230	7,600,595	Twitter-1.4B	41,652,230	1,468,364,884
Google	875,713	5,105,039	Freebase-500M	97,290,357	499,982,284
NotreDame	325,729	1,497,134	Freebase-1B	156,595,723	999,965,047
Stanford	281,903	2,312,497	LUBM-500M	115,561,430	500,002,176
LiveJ-20M	2,545,981	20,000,000	LUBM-1B	222,213,904	961,394,352

Graph datasets

Setup: Master:1, Slaves:9, Memory:64 GB

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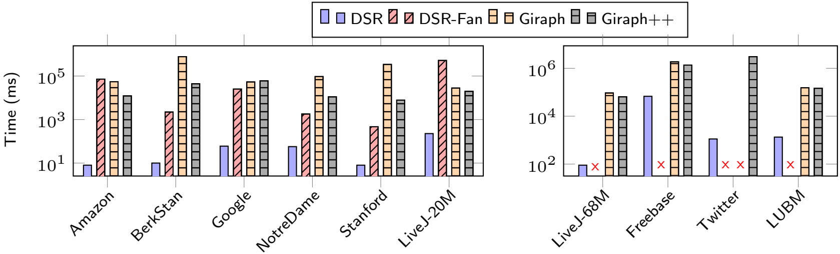

DSR is orders of magnitude faster than Giraph, Giraph++, and DSR-Fan

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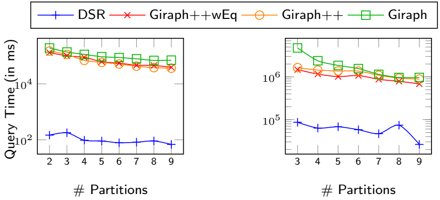

LiveJ-68 Freebase-1B

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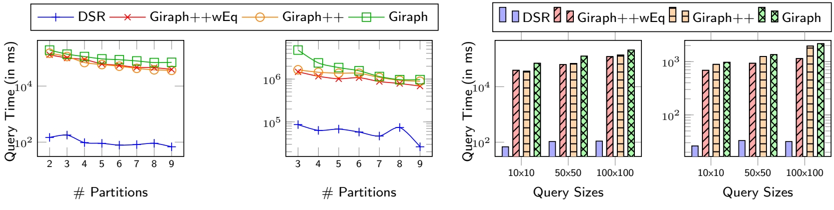

LiveJ-68 Freebase-1B LiveJ-68 Freebase-1B

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Thank you for your attention

References I

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Questions?

For more details, please visit my poster: 84